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METHOD

Enhancing marine wildlife observations: the application of tethered balloon systems and advanced imaging sensors for sustainable marine energy development

Alicia Amerson[1] · Darielle Dexheimer[2]

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Abstract

The Triton Initiative has evaluated environmental technologies and methodologies, focusing on the detection and tracking of marine wildlife, since 2018. This study builds upon an initial flight trial of a tethered balloon system (TBS) and sensor package conducted on behalf of the Triton Initiative in 2022, and further investigates the capabilities of a tethered balloon system (TBS)for detecting and monitoring marine wildlife, primarily focusing on gray whales (*Eschrichtius robustus*) and various avian species. Over 55.7 h of aerial and surface footage were collected, yielding significant findings regarding the detection rates of marine mammals and seabirds. A total of 59 Gy whale, 100 avian, and 6 indistinguishable marine mammal targets were identified by the airborne TBS, while surface-based observations recorded 1,409 Gy whales, 1,342 avian targets, and several other marine mammals. When the airborne and surface cameras were operating simultaneously, 21% of airborne whale and 34% of airborne avian detections were captured with the airborne TBS camera and undetected with the surface-based camera. The TBS was most effective at altitudes between 50 and 200 m above ground, with variable-pitch scanning patterns providing superior detection of whale blows compared to fixed-pitch and loitering methods. Notably, instances of airborne detections not corroborated by surface observations underscore the benefits of combining aerial monitoring with traditional survey techniques. Additionally, the integration of machine-learning (ML) algorithms into image analysis for marine wildlife detection enhances our capacity for processing large datasets, paving the way for real-time wildlife monitoring, which is currently limited by the time associated with human review of imagery. Currently, ML algorithms require more training datasets to be created from varied aerial platforms operating in many conditions to improve detection accuracy before they are comparable in cost and processing time to human image review. In our study for concurrent observations, the percentage of blows only identified by a human analyst was greater than the percentage uniquely detected by the algorithm. Notably, more unique detections by the ML algorithm occurred during daylight, suggesting that sun artifacts may hinder human detection performance during high glare, thereby highlighting the added value of ML under these conditions. This research lays the groundwork for future studies in marine biodiversity monitoring, emphasizing the importance of innovative aerial surveillance technologies and advanced imaging methodologies in understanding species behavior and informing conservation strategies for sustainable marine energy, offshore wind development, and other marine resource management efforts.

Alicia Amerson and Darielle Dexheimer contributed equally.

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✉ Alicia Amerson
alicia.amerson@pnnl.gov

Darielle Dexheimer
ddexhei@sandia.gov

1 Biological Sciences Division, Pacific Northwest National Laboratory, Sequim, WA, USA

2 Darielle Dexheimer, Sandia National Laboratories, Albuquerque, NM, USA

Graphical abstract

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Introduction

As various marine ecosystems increasingly face considerations for marine energy (ME) development, comprehensive environmental assessments have become necessary (Eaves et al. 2022). These assessments aim to evaluate the potential impacts of new technologies on energetically dynamic marine environments, particularly focusing on how marine wildlife interacts with ME devices. Disturbances from ME installations may lead to alterations in habitat use, behavioral changes, and shifts in population dynamics for key species, making it essential to provide field-tested recommendations for implementing environmental monitoring technologies and methodologies to understand these interactions (Amerson et al. 2022; Haxel et al. 2022; Hemery et al. 2022a, b; Reilly et al. 2022; Staines et al. 2022).

There is a growing interest in utilizing cost-effective monitoring technologies that can also be implemented with minimal to no impact on wildlife (Gibbs et al. 1999; Thomas et al. 2011; Christie et al. 2016; Marvin et al. 2016; Stephenson 2020). While these technologies are more easily adapted for terrestrial wildlife, they also apply to observations of marine wildlife interactions with ME systems (Bicknell et al. 2016; Danovaro et al. 2016; Wang et al. 2019). However, gaps remain regarding the efficacy of aerial monitoring methods, particularly in varied marine and coastal conditions (Amerson et al. 2023). Specifically, UAV monitoring of marine wildlife has been subject to limitations associated with noise and moving shadow from the aircraft (Álvarez-González et al. 2023), environmental factors such as visibility, sun glare, temperature, rain, and wind (Aniceto et al. 2018; Raoult et al. 2020; Álvarez-González et al. 2023; Courbis et al. 2023), detection reliability with depth (Hodgson et al. 2018), aircraft autonomy and flight time, and intensive data processing and human involvement in detecting wildlife (Oleksyn et al. 2021; Rodofili et al. 2022, 2024). It was hypothesized that tethered balloon systems (TBS) may ameliorate some of the limiting factors associated with using UAVs for marine mammal monitoring, such as a reduction in noise and shadow motion, decreased reliance on aircraft electronics which may inhibit UAV flights in rain, and increased flight time and autonomy. TBS generally exhibit similar limitations to UAV in that they do not operate in wind speeds in excess of 12 m s^{-1} and they require human interaction to operate. Recent efforts to advance the level of TBS autonomy and increase operational wind speed limits (Dexheimer et al. 2024), particularly at the relatively low flight altitudes required for marine wildlife monitoring, may be achievable by optimizing the balloon characteristics (White, 2024). This study also evaluated varied thermal imagers with respect to field of view and resolution using multiple TBS flight patterns and the ability of ML to reduce data processing cost and labor associated with TBS imagery.

In a previous study, the research team conducted an initial flight trial of a TBS and sensor package in La Porte, Texas (TX) (Amerson et al. 2023). During this study, no marine wildlife species were present. Therefore, there was a need to perform flights along a coastline with a known migratory path and a larger diversity of marine species. Furthermore, a consideration for the second deployment was to find an environment similar to areas of future ME development. An additional consideration was made to include flights during daylight and nighttime hours to evaluate the use of a TBS for ME environmental assessment over a 24-hour period. Lastly, accumulating a large dataset from the effort in La Porte, TX presented a challenge associated with aerial monitoring: increased processing and analysis time by humans. The need for reliable ML applications may reduce this processing and analysis time, but these systems are currently under development and require reliable data libraries (Kellenberger et al. 2018; Corcoran et al. 2021; Aguilar-Lazcano et al. 2023; Clarfeld et al. 2023; Sharma et al. 2023). A reliable source of data for ML may be obtained from analysis that has been processed through human observations (Stewart et al. 2023; Barlow et al. 2024).

This study aimed to address these gaps by integrating a TBS equipped with advanced imaging sensors to observe marine wildlife along the California coast, a critical migratory corridor for species such as gray whales and other marine mammals. Additionally, this study evaluated data collected by TBS sensors and human observations, reviewed various scan patterns and loitering altitudes, and leveraged ML programs to detect whale blows. By implementing ML, the goal was to compare the time and cost of data processing and analysis between humans and ML programs.

The significance of this research lies in its potential to provide technological and methodological recommendations for regulatory decision-makers and to contribute to diverse environmental monitoring technology solutions for the future development of ME and offshore wind energy installations. This study aligns with the U.S. Department of Energy (DOE) Water Power Technologies Office's (WPTO's) commitment to advancing sustainable energy systems in U.S. waters, recognizing that ME involves generating energy from marine resources, such as waves, tides, and currents (Garson 2023). To this end, innovative monitoring approaches are essential for effective environmental management. This study aimed to evaluate the capability of airborne thermal imagery from TBS in comparison to the wildlife detection capabilities of traditional human observations and surface-based thermal imaging. Human observations have historically been impaired at night and aerial and surface-based thermal imaging efforts have suffered from degraded performance in reduced visibility (Baldacci et al. 2005; Weissenberger and Zitterbart 2012; Verfuss et al. 2018). Prior studies suggest that aerial monitoring could increase the detection rates of large marine species in comparison to human or surface-based observations alone (English et al. 2024; Farinelli et al. 2024; Panigada et al. 2024); however, the specific capabilities of thermal imager-equipped TBS in low visibility and night conditions remain fully unexplored.

Preliminary tests were conducted to assess sensor performance in limited visibility under controlled fog simulations at Sandia National Laboratories (Sandia) to validate the methodology. This foundational work underscores the potential of TBS technology for monitoring marine wildlife under challenging conditions. Subsequently, a full TBS field operation was executed in Carmel, California, with the following objectives: (1) to detect live marine wildlife within the study area during both day and night, (2) to compare detection rates between the TBS and sensor packages at various altitudes against human observations from a land-based station, (3) to determine whether scanning or stationary imaging methodologies on the TBS at altitude optimize wildlife detection, and (4) to evaluate the performance of ML algorithms in comparison to human post-collection analyses of TBS-collected imagery.

By providing robust, scientifically grounded data, this research aims to contribute to existing knowledge regarding aerial technologies and methodologies for detecting and monitoring interactions between marine wildlife and ME systems. The subsequent sections will detail the methodology, results, and recommendations based on lessons learned and the future steps to advance TBSs and sensors, with an emphasis on aiding sustainable ME and offshore wind development.

Methods

TBS and metocean sensors

Fifty-three hours of TBS flights were conducted by Pacific Northwest National Laboratory (PNNL) and Sandia at the Marine Pollution Studies Laboratory (MPSL) at Granite Canyon near Carmel, California, from January 25–29, 2024. The MPSL, which is jointly administered by the National Oceanographic and Atmospheric Administration (NOAA) and the University of California at Davis, is ideally located to monitor migrating gray whales on their southerly progression during the California winter at 36.44°N, 121.92°W and 21 m mean sea level (msl). TBS flights occurred between 0 and 300 m above ground level (agl; 21–321 m msl) during daylight and nighttime conditions, as summarized in Table 1.

The TBS was composed of a 128 m^3 helium-filled aerostat powered by a 5 hp direct current (DC) permanent magnet motor controlled by a reversible regenerative driven variable-speed controller. The TBS operated airborne imaging sensor packages, as described in the next subsection (Fig. 4), day and night during varying atmospheric conditions and flight altitudes, as shown in Fig. 1. The temperature, relative humidity, and altitude were measured with an InterMet iMet-4 RSB radiosonde on the TBS. Visibility was measured with a surface-based Campbell Scientific CS120A visibility sensor and typically decreased during daylight hours, as shown in Fig. 2. Based on the results of a study conducted in Sandia's Fog Tunnel in December 2023 (Dexheimer et al. 2024) the radiometric output of the TBS thermal imagers was expected to become increasingly inaccurate with decreasing visibility, and target detection to be impaired in reduced visibility because of the increased homogeneity within the radiometric image. Surface wind and wave properties were measured by the CODAR SeaSonde system at Granite Canyon, which is a high-frequency radar that measures surface currents from sea echo, in addition to deriving information on wind and wave properties from the sea echo.

Imaging sensors

An ICI Mirage 640 P mid-wavelength infrared (MWIR) imager (Fig. 4d) was used with 27 and 11 mm lenses, and an ICI 8640 long-wavelength infrared (LWIR) imager (Fig. 4c) was used with a 50 mm lens. The Mirage 640 costs roughly 5 times more than the 8640 and uses a cooled sensor with enhanced thermal imaging capabilities in colder temperatures. Both cameras were tested to determine if the Mirage provided increased detection capability. Multiple lenses were also tested to assess the comparative virtues of field of view (FOV) and resolution on the detection capability. At the start of each flight day, each thermal imager was calibrated at four pitch angles against a reference heated water bath with a stated temperature stability of ± 0.07 °C, as shown in Fig. 3. The emissivity value that allowed the radiometric temperature to match that of the calibration bath was recorded for each pitch and camera and lens combination to allow accurate radiometric output to be produced from the thermal images during post-processing.

A Sony UMC-R10C camera (Fig. 4d) was used to provide a visible reference during thermal imaging. Tallysman HC872 helical antennas and Hemisphere Vega 28 global navigation satellite system (GNSS) compass boards (Fig. 4b) were used with the airborne Gremsy T7 camera gimbal to determine the distance to the imaging target. A full description of the imaging sensors and methodology

Table 1 TBS flights occurred between 0–300 m Agl (21–321 m msl) during daylight and nighttime conditions

Altitude (m agl)	50	100	150	200	250	300
PST / UTC Hour						
8 / 16	X					
9 / 17	X					
10 / 18		X	X	X		
11 / 19	X	X		X	X	
12 / 20	X		X		X	
13 / 21	X			X	X	
14 / 22	X	X				X
15 / 23		X	X			
16 / 0		X		X		
17 / 1					X	
18 / 2	X		X			
19 / 3		X	X	X		
20 / 4				X	X	
21 / 5		X	X			
22 / 6	X	X	X	X	X	
23 / 7	X	X				

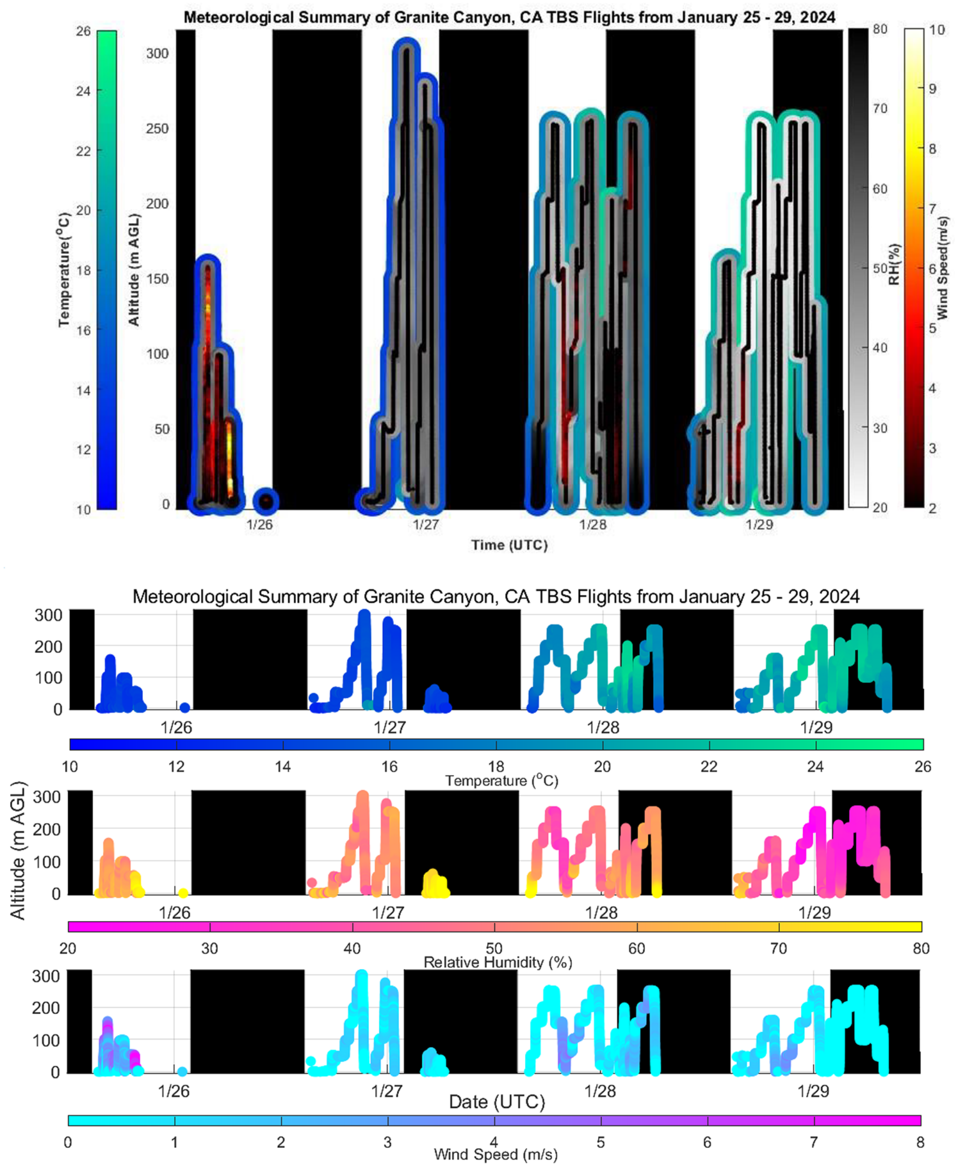

Fig. 1 The TBS operated airborne imaging sensor packages day and night during varying atmospheric conditions and flight altitudes

is available in Dexheimer et al. 2024. A RED Komodo 6 K cinema camera (Fig. 4e) was used with a Canon EF 100–400 mm L-series zoom lens to capture high-resolution images and video of marine wildlife. All imaging acquisition devices were time-synced daily.

TBS operations

Over 55 h of footage were collected and processed during the study, as detailed in Table 2. Initially, the TBS carried out two opportunistic scanning patterns, which required the camera's FOV to overlap with the position and timing of the present wildlife.

A variable-pitch scan from shoreline to shoreline was performed using the Mirage camera and 27 mm lens as depicted in Fig. 6. The pitch decreased from −3° to −75° below the horizon, with a −3° pitch equal to a 1.9 km distance to a target with the balloon 100 m agl. The balloon ascended in 50 m increments from 50 m to 300 m, with the pitch decreasing in increments corresponding to a change in the observed distance equal to half the vertical FOV. As the balloon ascended, the scan was initiated at steeper pitch angles, where a cutoff size of 4 pixels for an expected 7 m long target was reached based on the distance to the target. The camera operator maintained the camera at a fixed heading and pitch angle using in-flight data streaming from the differential GNSS antennas on the camera gimbal in addition to the real-time gimbal controller display. This scan pattern required 135 min to complete, with the scan at each altitude taking approximately 14 min. During the scan, a still image and 10 s video clip were continuously captured. The

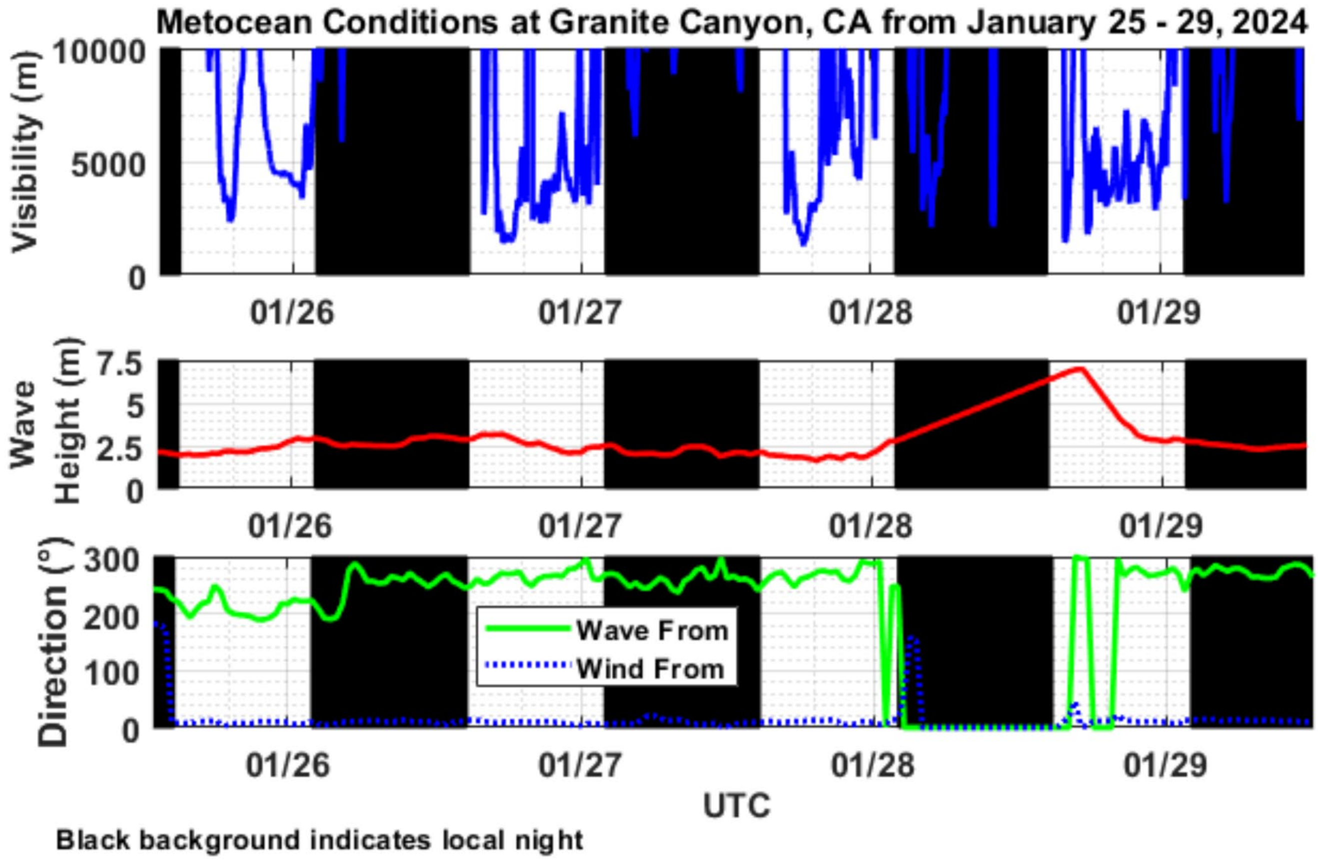

Fig. 2 Visibility was measured with a surface-based Campbell Scientific CS120A visibility sensor and typically decreased during daylight hours

Fig. 3 At the start of each flight day, each thermal imager was calibrated at four pitch angles against a reference heated water bath with a stated temperature stability of ±0.07 °C

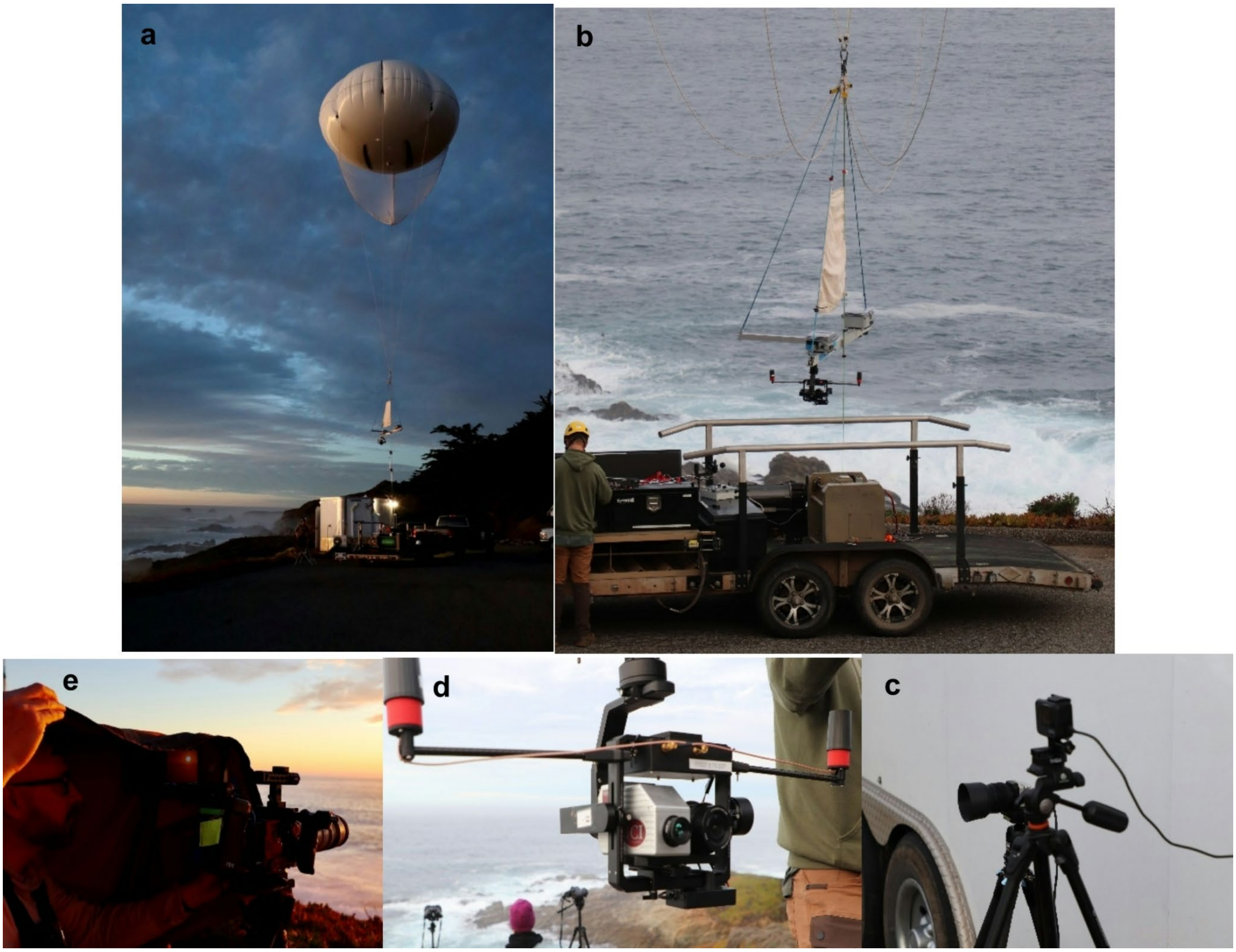

Fig. 4 Clockwise from top left: (**a**) The airborne camera boom launching on the TBS; (**b**) the camera boom, suspended gimbal, and GNSS differential antennas above the TBS winch; (**c**) the ICI 8640 camera continuously operated at the surface from January 27 to January 30; (**d**) the ICI Mirage and Sony R10C cameras on the Gremsy T7 gimbal with the differential GNSS antennas and Vega 28 positioning board; and (**e**) the RED camera

Table 2 Throughout this study, 55.7 h of footage were collected from the surface and aloft

Location	Camera and Lens	Raw	Processed	Dates	Duration (hours)	Processing Method
Total Surface	ICI 8640 and 50 mm	4.49 TB	292 GB	January 27–30	38.7	Human, ML
Airborne	ICI 8640 and 50 mm	133 GB	10.9 GB	January 25–26	2.0	
Airborne	Mirage and 27 mm	687 GB	44.1 GB	January 25–29	11.2	
Airborne	Mirage and 11 mm	234 GB	6.69 GB	January 28	3.8	
Total Airborne	All	1.03 TB	61.7 GB	January 25–29	17.0	Human
Total Footage	All	5.52 TB	353.7 GB	January 25–29	55.7	

length of this scan pattern taxed the manual dexterity and visual endurance of the camera operators, so the scan pattern was revised to use a fixed pitch of −4° with the Mirage camera and either a 27 mm–11 mm lens loitering at 50 m increments between 50 and 250 m agl. The −4° pitch radius was perceived to coincide with the region of most abundant marine wildlife based on camera operator observations during the study. This perception was later confirmed by the ML algorithm's analysis of captured video determining that 75.8% of whale blows were detected between 1 and 2.5 km from the surface-based camera. The variable- and fixed-pitch scan patterns were conducted for over six and almost nine hours, respectively, during the TBS flight campaign. Locations of the airborne camera on the TBS are depicted in Fig. 5.

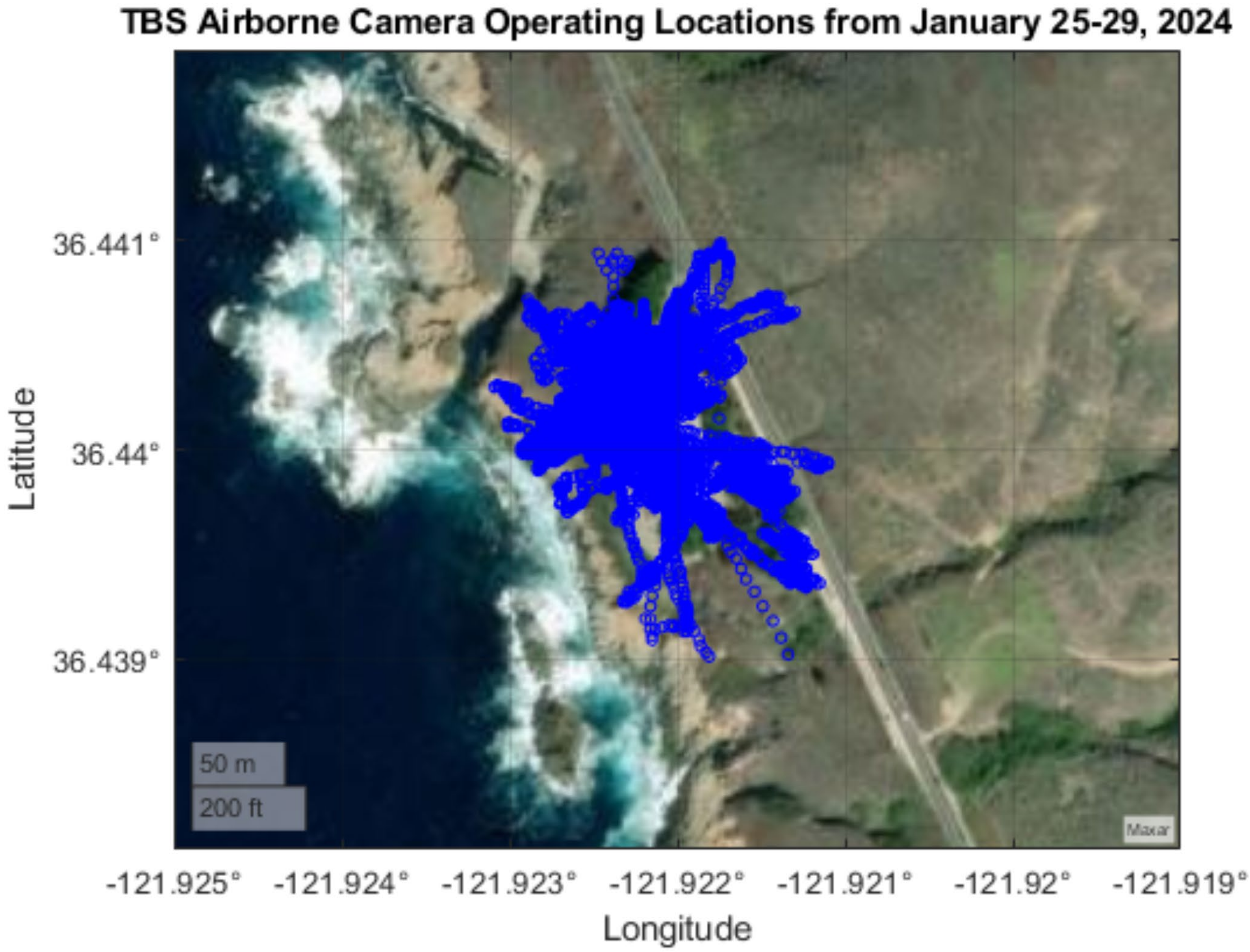

Fig. 5 TBS in-flight camera locations at Granite Canyon

The TBS alternated the opportunistic fixed-pitch scan with an observer-driven loitering pattern, which stationed the Mirage camera with the 11–27 mm lens at a fixed altitude in 50 m increments between 50 and 250 m agl for 15–30 min with the camera pointed perpendicular to the shoreline on a 237° heading. The operator would look for any potential targets in the controller display within this period, while an additional visual observer simultaneously scanned for targets. If a target was identified by the observer, the camera operator would be verbally guided until the target was in frame; then, the target was tracked as a still image, and 10 s video clips were continuously captured. If no targets were identified, the still image and 10 s video clips were continuously captured throughout the scan. When the TBS was ascending or descending to a new flight level during all flight patterns, scanning would be suspended, and the airborne camera would be fixed on a 237° heading. Ascending or descending 50 m between flight levels generally occurred in 100 s. The loitering pattern was conducted for over 25 h during the campaign. Through the use of the scanning and loitering patterns, we intend to study the rates of comparative target detection between both operating methodologies. A surface-based ICI 8640 thermal imager was operated continuously from January 27 at 14:30 to January 30 at 03:00 on a 237° heading to provide a comparison of detection rates with the airborne thermal imagers.

Target detection and visual observations

Airborne and surface thermal videos were imported into ICI's IR Flash Pro software and exported as .mp4 files, which were then watched at a 3× playback rate. Detected individuals were recorded with respect to species and time. NOAA visual observers independently conducted surface-based gray whale surveys at MPSL with binoculars from 07:30 to 16:30 on Monday through Friday from January 22 to February 1, 2024, with Thursday the 25th and Friday the

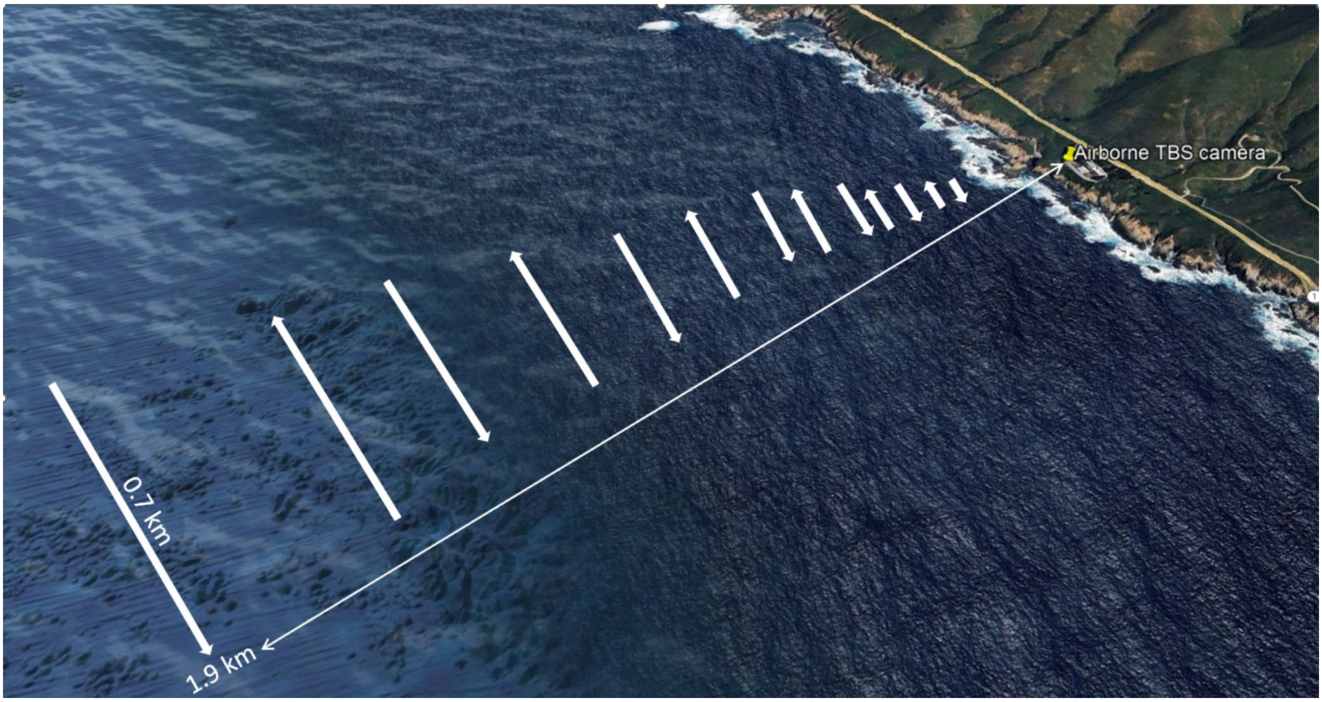

Fig. 6 Depiction of a variable-pitch scan at a TBS altitude of 100 m agl. The direction of an arrow indicates the direction of a scan

26th overlapping TBS flights. NOAA's recorded sightings were compared with TBS thermal-imagery-based detections to determine if and when TBS-based observations may provide added value. RED camera video was encoded with RED's proprietary RedcodeRAW codec to preserve image quality and was color-graded and converted to Rec709 .mp4 video files using Adobe Premiere Pro and Media Encoder software. RED camera video footage was evaluated to compare 2 K, 4 K, and 6 K resolutions in terms of visual detail and clarity. The analysis presented in Fig. 7 illustrates

Fig. 7 RED camera video footage comparison at 2 K, 4 K, and 6 K

the distinct image quality and detail associated with each resolution. Higher resolutions, particularly 4 K and 6 K, provided enhanced depth of field, which may improve the detection and detail of whale observations. These findings highlight the role of a higher resolution in improving the detection of whale blows and other marine wildlife.

Machine-learning detection

Toyon Research Corporation (Toyon) was provided with converted 8-bit .mp4 files of surface and airborne camera footage. Infrared video was processed in Toyon's Whale Spout Detector using both human-developed algorithms and artificial intelligence (AI) techniques. The human-designed algorithms served as a detector that identified possible locations of whale blows that were then fed to the AI model, which classified them as either whale blows, vessels, or other objects. The detector functioned by first building a background model of the scene to look for statistical anomalies using a single frame of data. Once an anomalous group of pixels was located, it triggered a tracking mechanism that followed the development of a candidate blow so that only objects that were similar in brightness and duration to a whale blow were passed along to the AI model. The AI model was a novel design developed at Toyon based on a convolutional 3D (C3D) architecture. Multiple 3D convolutions were performed so that both spatial and temporal features could be extracted. The model had been trained using thousands of samples of whale blows, vessels, and clutter. Details on the training of similar human-designed whale blow detection software are available in Sullivan et al. 2020. The classifier used to process detections in this study was built using samples taken from Table 3. The numbers in the table indicate the number of samples from that dataset in the category specified by the column headings used to train the neural network classifier. The first three rows in the dataset were data collections made from shore-based cameras and the last three data collections were made using surface-vessel-based cameras. All data collections were performed using uncooled LWIR cameras and each sample was a short video clip that allowed for the extraction of spatial and temporal features.

The trained model was embedded in the C++software of Whale Spout Detector using the Open Neural Network Exchange (ONNX) format. The ONNX model allowed for seamless integration into C++software, enabling real-time, efficient operation on various hardware platforms and allowing for much faster than real-time operation on the collected footage.

Table 3 Description of samples used to build Toyon Whale blow detection model

	Blows	Vessels	Clutter
Sakhalin 2017	14,356	0	86,844
NOAA2014	423	0	257
NOAA2015	1800	0	920
Ttn 2022	164	208	4740
Mrln2022	40	0	0
Snn 2022	938	1701	4777

Results

Throughout this study, 55.7 h of footage were collected from the surface and aloft, as summarized in Table 2. From the airborne TBS, 59 Gy whale, 100 avian target, and 6 indistinguishable marine mammal sightings, which were either sea otter or harbor seal (*Phoca vitulina*), were observed, while 1409 Gy whales, 1342 avian species, 33 sea otters, 11 common dolphins (*Delphinus delphis*), and 19 indistinguishable mammals were observed by the more continuous surface-based thermal imager. Avian detection includes seabird and birds of prey species. As shown in Fig. 8, most airborne whale sightings occurred in midmorning local time with a secondary peak in the early afternoon. Airborne avian sightings were distributed throughout the day and night, with peak observations occurring in the early afternoon. Harbor seals and sea otters were sighted in the morning. Most surface-based (non-TBS-derived) gray whale sightings occurred between sunset and midnight local time with a secondary peak in the afternoon. Surface avian observations peaked around midday and near sunset, and sea otter, common dolphin, and indistinguishable mammal sightings were most often observed during the day from midmorning to late afternoon. The only period of overlap between the airborne TBS and NOAA human observations occurred on January 25 and 26. The airborne TBS observations exhibit more diurnal variability than the human observer observations, but both methodologies indicate a similar magnitude of observations and decreased whale sightings in the late afternoon, likely attributed to changing environmental conditions. These conditions include increased surface glint from the sun setting, heightened wind speeds, and elevated Beaufort scale conditions. Toyon machine-processed and

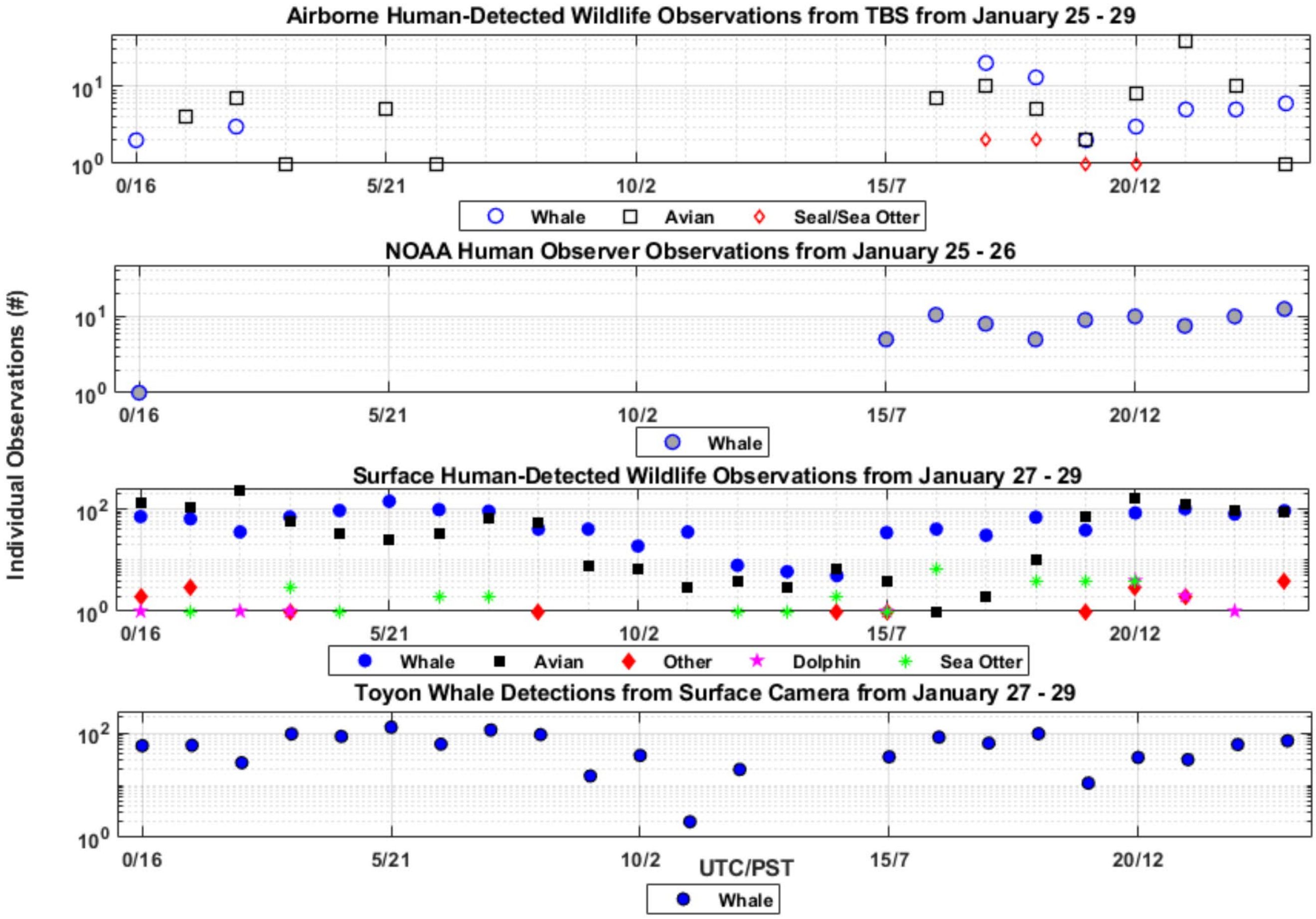

Fig. 8 Total hourly human-detected airborne camera, human-observed, human-detected surface-based camera, and machine-learning-detected surface-based camera wildlife observations at MPSL from January 25–29, 2024

human-processed detections from the surface camera exhibited remarkably good diurnal agreement, lending confidence to both methods.

In Fig. 9, TBS flight altitudes were normalized by the total flight time and compared with the altitudes of whale detection normalized by total whale detections. A lower percentage of whale detections occur above 200 m in relation to the total flight time at or above 200 m. Based on real-time experience during the field campaign and post-processing, the reduced resolution at these higher flight altitudes resulted in difficulty in target identification. In contrast, a greater number of whale detections occurred at TBS altitudes of 50–100 m. This relatively low altitude indicates that marine mammal observations may not require aircraft and could occur from coastal instrumented towers or elevated structures, as well as offshore wind infrastructure.

Of the 47 separate airborne captures of 59 total whales, 14 captures occurred when both the surface and airborne camera were operating simultaneously between January 27 and 29. Three of these fourteen capture events, or 21%, did not result in a surface whale observation within 3 min, which we interpret as an airborne detection/surface miss case. As shown in Fig. 10, the median TBS altitude during the three-whale airborne detection/surface miss cases was 200 m, compared to a median TBS altitude of 153 m for all 14 simultaneous whale detection events, which suggests that additional observations may have been captured if the camera on the TBS had a larger FOV.

The surface 8640 camera was expected to resolve a 7 m whale target into the minimum perceived detectable number of pixels, 4, at a 1.5 km distance to target. The airborne Mirage and 27 mm lens resolved the same 7 m target in 4

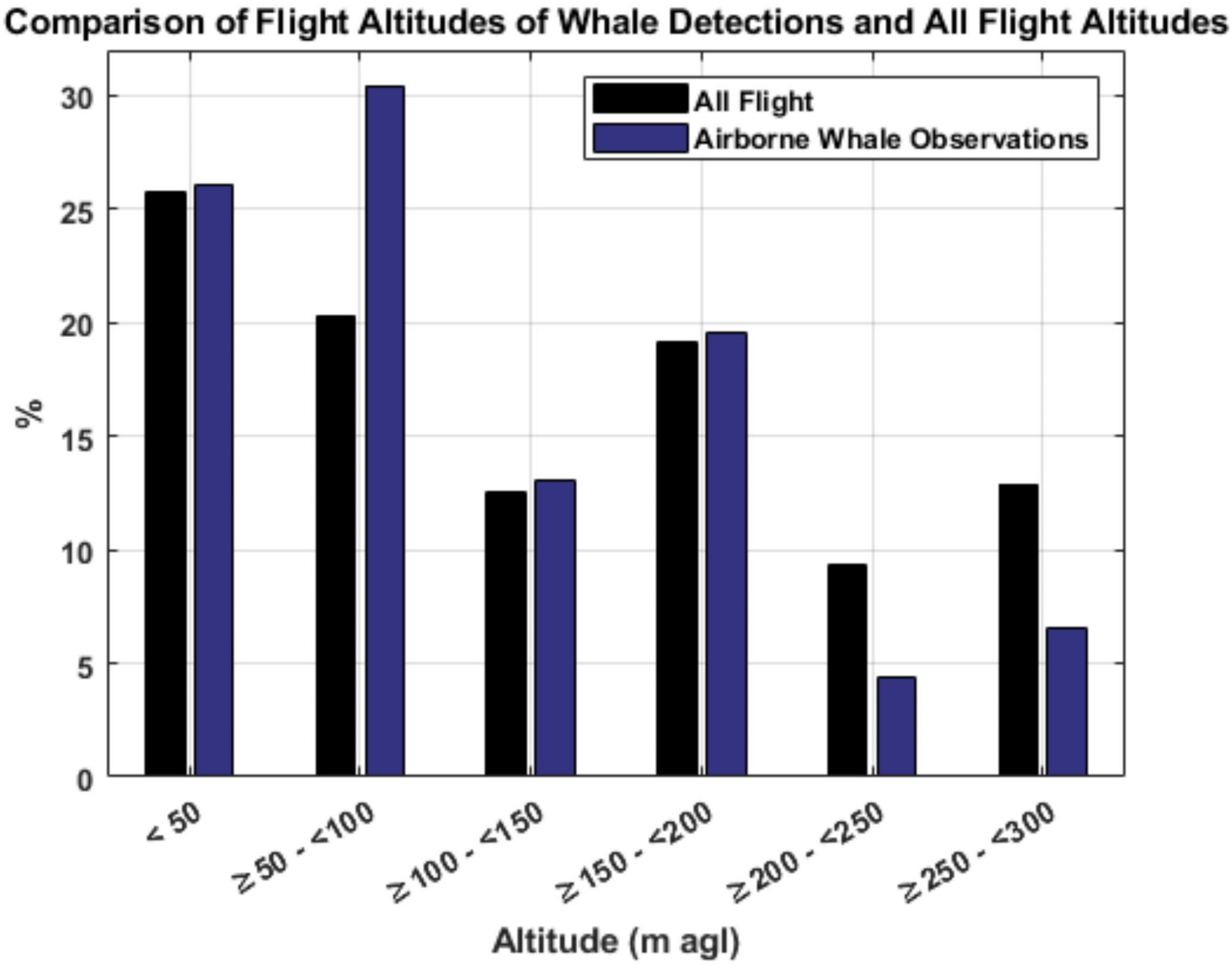

Fig. 9 TBS flight altitudes were normalized by the total flight time and compared with the altitudes of whale detection normalized by total whale detections

pixels at a 3.3 km distance to target. No whale blow observations were made with the Mirage and 11 mm lens, which resolved a 7 m target in 4 pixels at a 1.25 km distance to target. Figure 11a and b show an airborne detection/surface miss case observed with the TBS loitering at 200 m agl on January 28 at 23:47:11. The whale blow, circled in red, is observed at roughly half of the resolvable 3.3 km distance to target of the airborne Mirage camera (Fig. 11a) and is beyond the 1.5 km distance expected to be resolved by the surface-based 8640 (Fig. 11b).

Of the 68 separate airborne avian captures, 62 captures occurred when both the surface and airborne cameras were operating simultaneously. Of these 62 capture events, 21, or 34%, were airborne detection/surface miss cases. The median TBS altitude during the 21 avian airborne detection/surface miss cases was 57 m, compared to a median TBS altitude of 102 m for all 62 simultaneous avian detection events. Because of the reduced target size of avian observations compared to whale observations, target detection at distance is limited, and it is likely that the increased FOV of the airborne Mirage camera resulted in observations that were not detected by the surface 8640 camera and 50 mm lens. Figure 12a and b show an airborne avian detection/

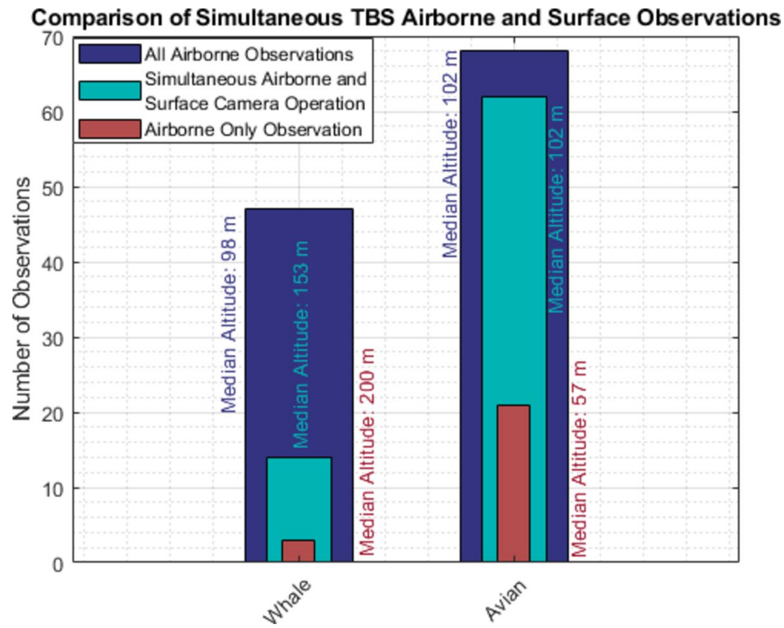

Fig. 10 Comparison of simultaneous TBS airborne and surface observations to analyze detection success rates, highlighting instances where airborne cameras captured whales not observed at the surface despite successful airborne detection

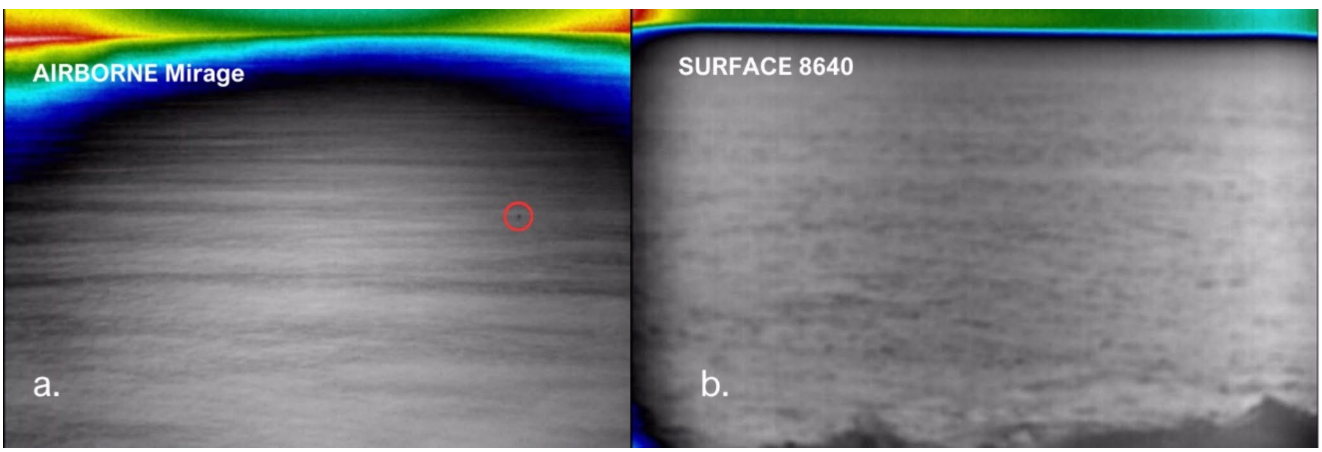

Fig. 11 (**a**) The airborne Mirage sensor detection of a whale blow (red circle). (**b**) The detection is not visible in the surface 8640 camera image

surface miss case observed with the TBS loitering at 50 m agl on January 28 at 16:33:14, where the target was beyond the FOV of the surface-based 8640. At a 700 m distance to target, the surface-operating 8640 field dimensions were 134 m × 107 m, compared with 611 m × 489 m for the airborne Mirage and 11 mm lens.

Of the 68 airborne avian captures, 15 were collected with the 11 mm lens on the Mirage and 53 were collected with the 27 mm lens, corresponding to similar respective detection rates of 4.0 and 4.7 avian detections per hour. The lens choice for avian detection should weigh the target size and the required resolution against the FOV. Although avian targets are small in comparison to whale blows, they are more easily identified because of their typically constant motion and trajectory.

Images of a simultaneous airborne whale detection/surface detection case observed when the TBS was engaged in fixed-pitch scanning at 150 m agl on January 29 at 02:03:46 are shown in Fig. 13a and b. A lens flare is visible in the lower left corner of the airborne image.

As depicted in Table 4, a comparison of the scan patterns indicates that the variable-pitch scan pattern resulted in the highest rate of whale blow detections per hour. However, the variable-pitch scan pattern was only used on January 25 and 26 before it was replaced by alternating shorter periods of fixed-pitch scanning bookended by longer loitering periods. Because of the limited amount of potential testing time on site and the uncertainty related to the peak of the migratory rate, the variable-pitch scan pattern was replaced by the

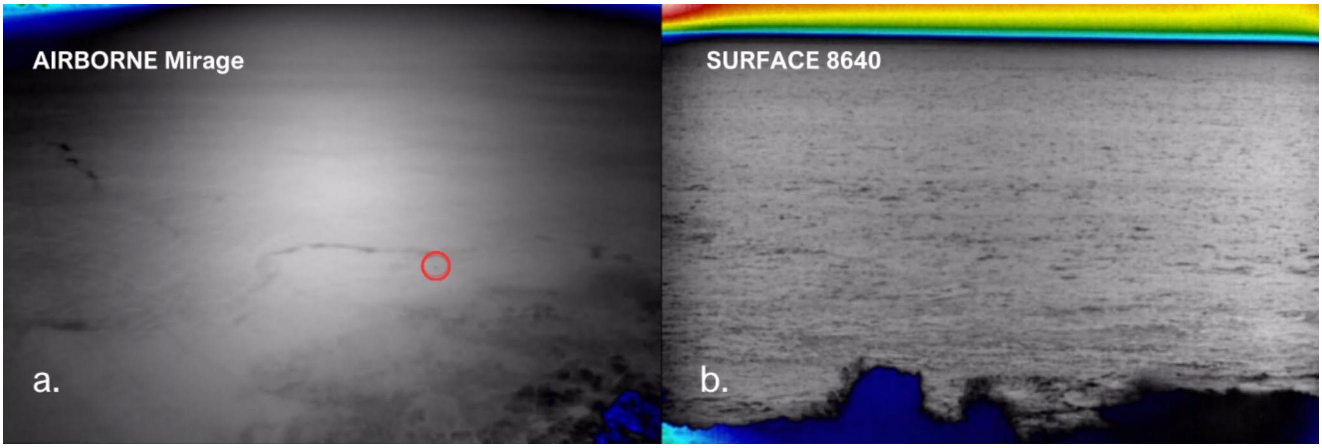

Fig. 12 (**a**) An airborne avian detection by the Mirage sensor, circled in red. (**b**) The detection is not shown in the 8640 simultaneous sensor image because the target was beyond the field of view

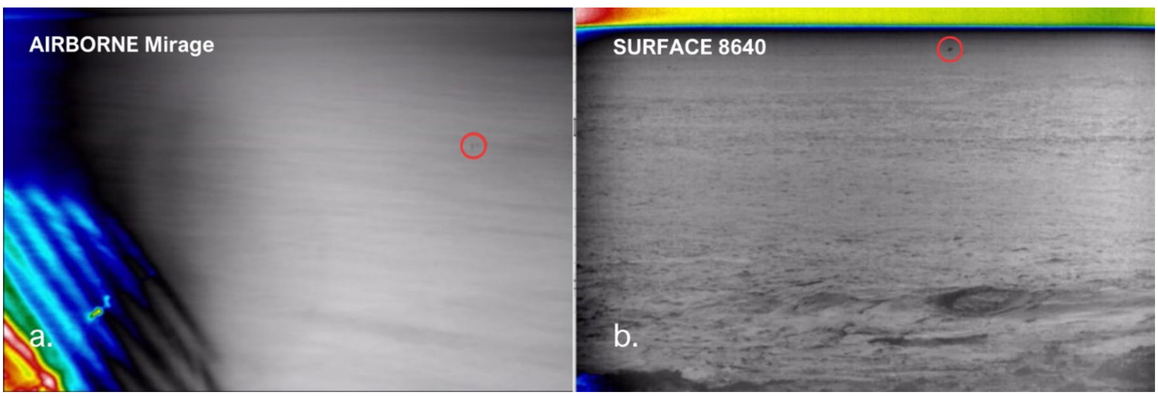

Fig. 13 Images of an airborne whale detection (**a**) and surface detection (**b**) case observed when the TBS was engaged in fixed-pitch scanning at 150 m agl on January 29 at 02:03:46. The whale blows are circled in red in both images

Table 4 Table of scan patterns: flight hours, Whale blow detections, and avian detections comparing detection rates across scan patterns

Scan pattern	Flight hours of Use	Whale blow detections per hour	Avian detections per hour
Variable pitch	6.1	4.7	0.4
Fixed pitch	8.7	1.0	2.2
Loitering	25.5	0.3	1.7

other two patterns because of the lengthy 135-minute period required to complete the scan. It should be noted that while the TBS conducted 53 h of flights between January 25–29, marine mammal imaging only occurred for approximately 40 h. The additional 13 h of flight time were typically spent troubleshooting or updating airborne instrumentation or occurred when it was difficult for the camera operators to see into the setting sun beginning about 90 min prior to sunset or when the solar elevation reached 15°.

To determine if the variability in whale blow detection rate is related to the TBS scan pattern or migratory intensity, we reference the NOAA human observer data shown in Fig. 15. Human-based whale surveys were generally conducted from 07:30–16:30 PST on weekdays from January 22 to February 2, which overlapped the TBS observations on January 25–26. On January 25, no human-based whale observations were made from 12:00–15:00 PST. All hours of operation for each observing method (human observer, surface camera, airborne camera) are summarized in Fig. 14.

A daily mean of 79 whale sightings were recorded in the human observations, with the mean on January 25 and 26 alone equaling 81 sightings per day. Since the mean number of whales observed on January 25 and 26 was consistent with the mean over the nine-day period, this indicates that the variable-pitch method has the greatest efficacy at identifying whale blows from the airborne TBS. The fixed-pitch and loitering patterns were alternated from January 27–29, so any variability in the migratory activity would be anticipated to impact the detections per hour for both patterns equally. While the least complex to execute or potentially automate in future iterations of this system, loitering exhibited the least efficacy for whale blow detection. For avian detection, the detection rate across the three scan patterns is relatively more uniform. Given that seabird populations tend to exhibit stable daily behavioral patterns rather than significant fluctuations due to migration or other factors, the fixed-pitch and loitering scan patterns might be more effective for detecting seabirds compared to the variable-pitch scan pattern. These scan patterns likely offer more reliable opportunities for detection under these stable conditions.

Sandia's student interns processed all 55.7 h of surface and airborne video footage at a rough cost of $65 per hour of footage. The advantages of human processing include the ability to process scanning or stationary footage and the ability to process the footage with respect to any identifiable animal species. The disadvantages are that human processing is tedious and time- and labor-intensive and requires significant data storage space that can be cumbersome to share between users. Toyon ML algorithms could not be run on the TBS airborne footage because the camera moved from one scene to another. The ML software builds a background

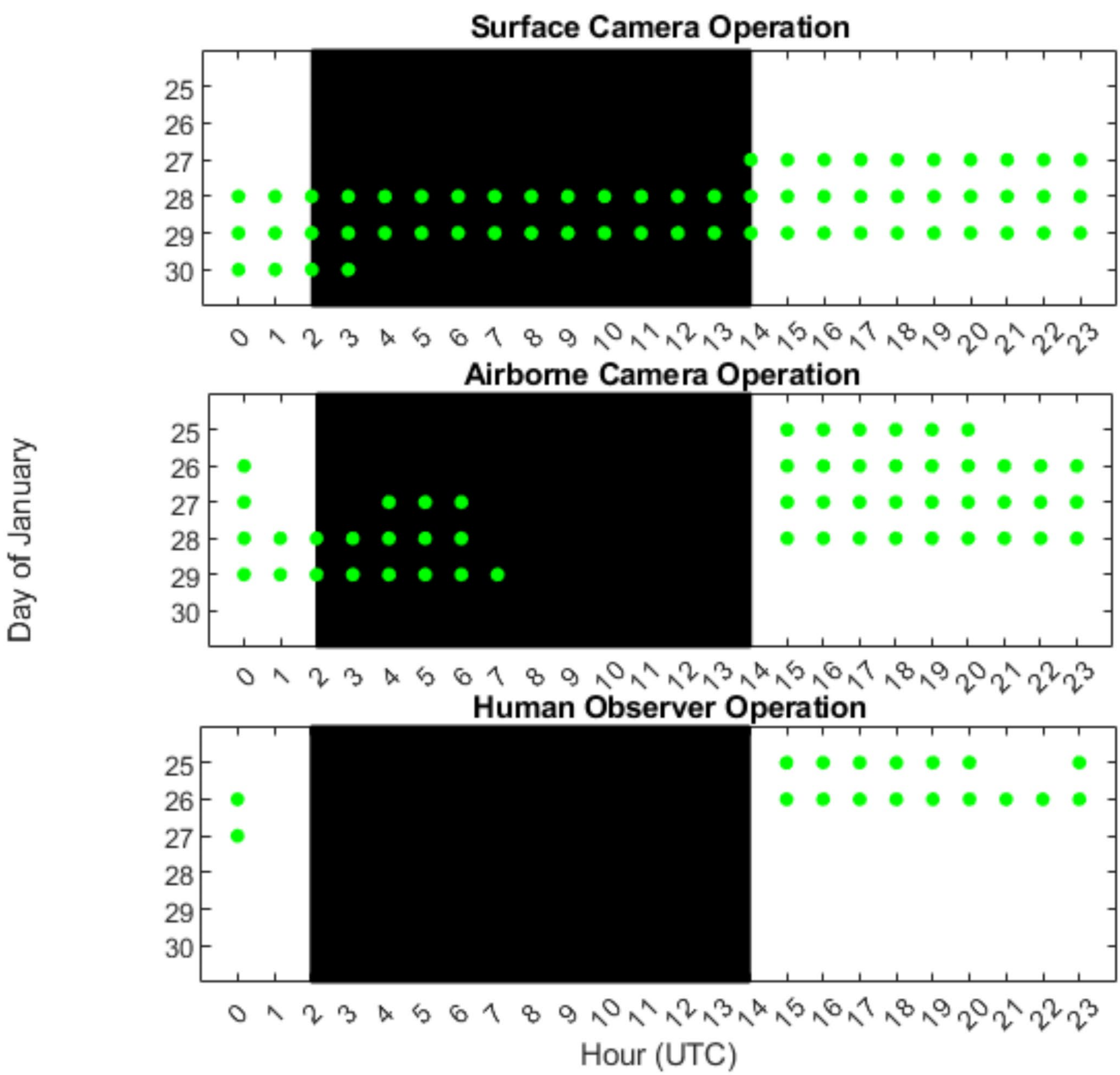

Fig. 14 Operation of each observational platform (surface thermal imager, TBS-operated airborne thermal imager, human observer) is indicated by the presence of a green dot

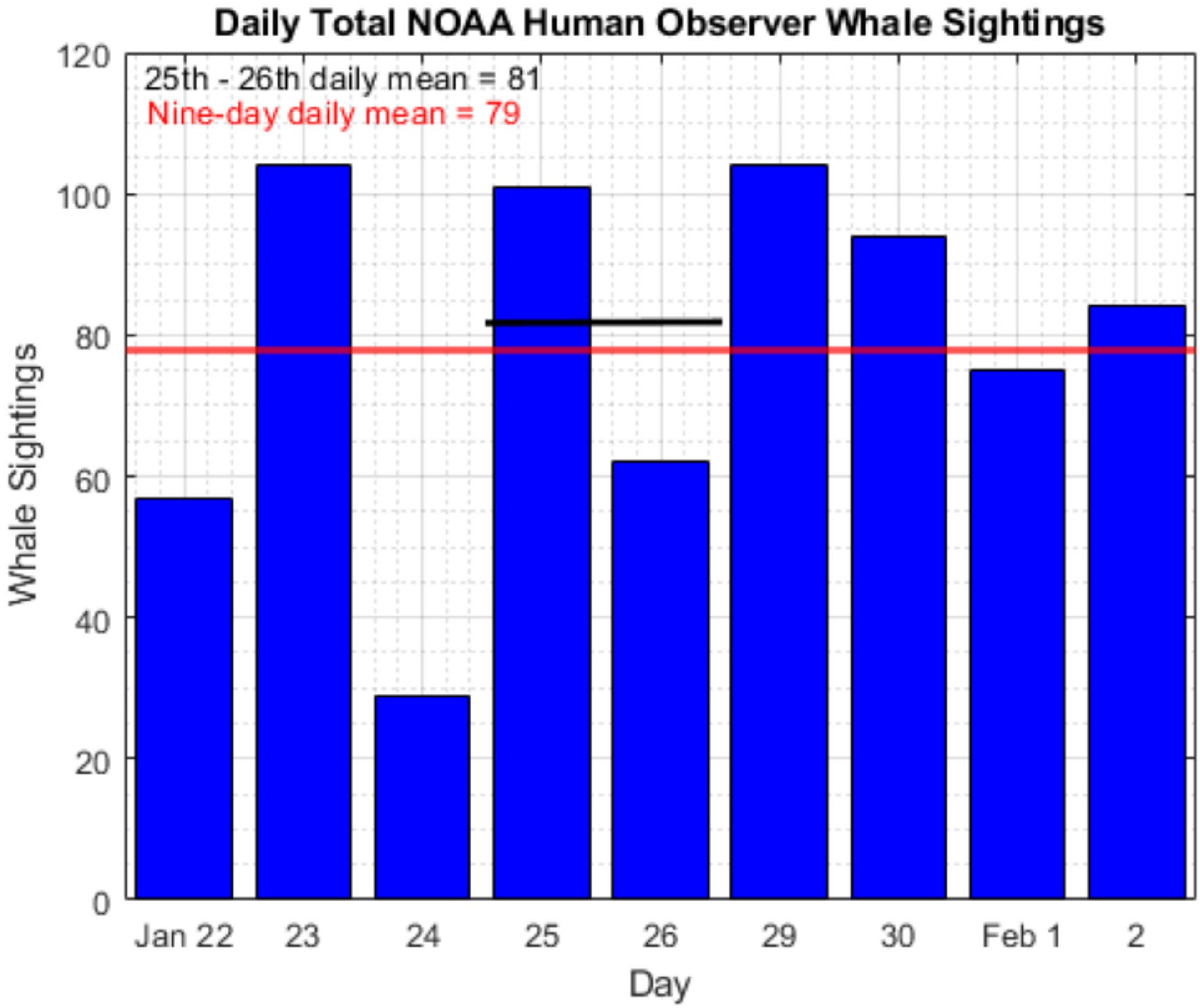

Fig. 15 Daily total NOAA human-observed whale sightings: Tracking the number of whale sightings recorded by NOAA observers over time

model of the ocean to detect whale blows and will not operate if the camera is moved more often than every few minutes. This dependency may limit the future adaptability of this automated detection method for use with active scanning patterns or from non-static platforms. Currently, ML algorithms are significantly more expensive than human processing conducted by unspecialized labor and have a rough hourly cost that is 5 times greater than the human processing costs incurred during this study.

Toyon Whale Spout Detector identified 1,281 whale blows in surface imagery collected between January 27 at 15:02 and January 29 at 23:55, as shown in Fig. 16. Human processing resulted in 1,121 detection events and 1,409 individual whale blows detected in surface imagery between January 27 at 14:35 and January 30 at 02:54. An important difference to note between human processing and the Toyon detector is that in human processing multiple blows could exist in a single detection, where the Toyon detector identified a single blow for each detection. Almost 69% (879) of the Toyon blow detections occurred within 3 min of a human processing detection, indicating that most blows detected by the Toyon detector ("Detections" bar in Fig. 16) were also detected by human analysts ("Detected by alternate method" bar in Fig. 16). In comparison, 591 or almost 53% of surface detections occurred within 3 min of a Toyon detection, indicating a greater number of detections occurred uniquely from human analysts in comparison to unique detections from the Toyon detector. As depicted in Fig. 17, an increased percentage of Toyon detections that were not detected by human analysts occurred during daylight, indicating that sun artifacts may have contributed to Toyon detections missed by human observers. This

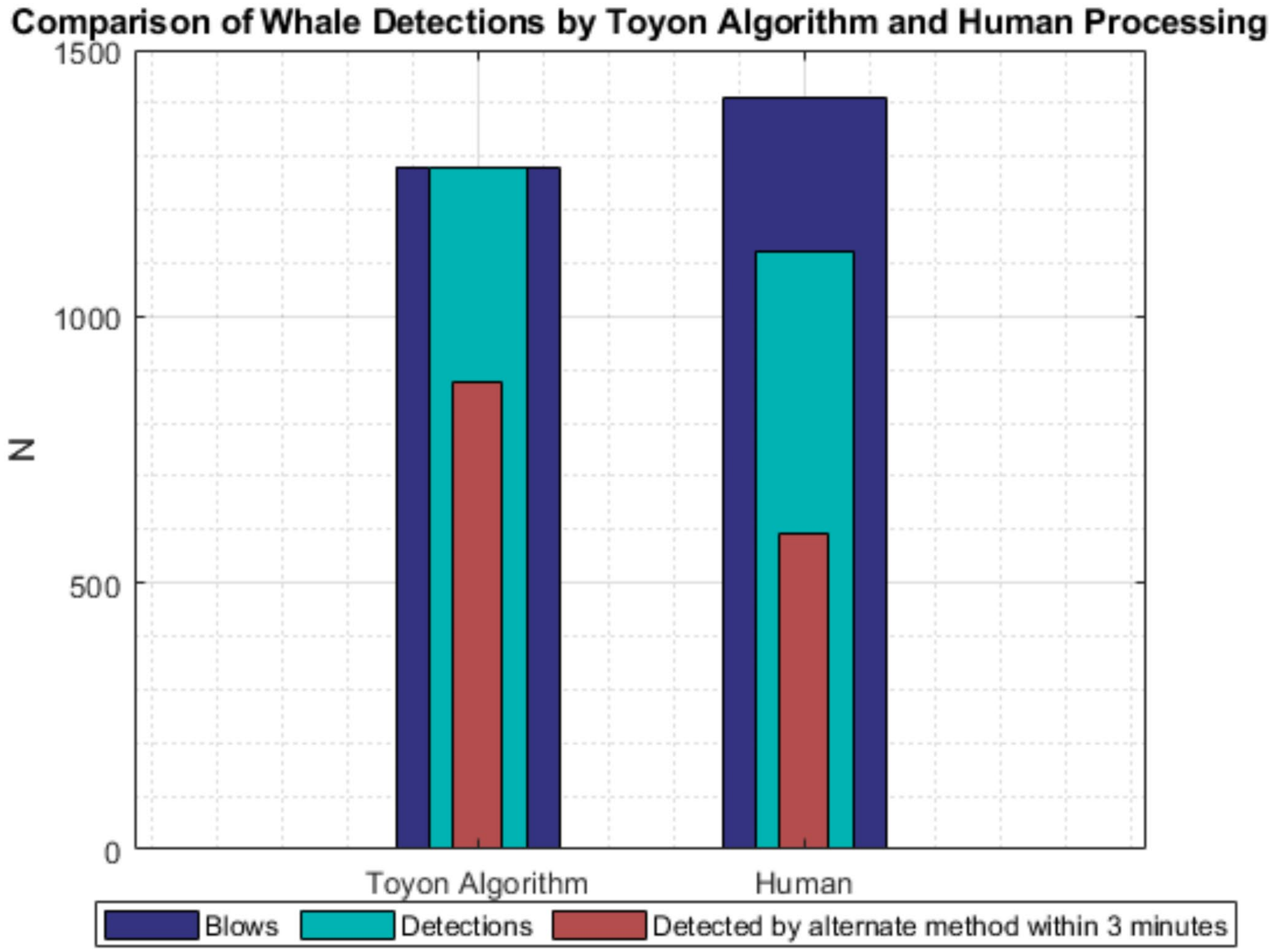

Fig. 16 The numbers of individual whale blows, detection events (which may be composed of multiple blows in the case of human processing), and detections by the alternate processing method within 3 min for the human analyst and Toyon algorithm for surface 8640 camera video processing

indicates a potential benefit of using ML algorithms on daylight imagery when human analysis may be impaired. Whale Spout Detector also estimates the range, coordinates, and bearing of a detected blow. Out of the total blows detected by the surface-based camera, 75.8% of blows were detected between 1 and 2.5 km, which informs the design criteria for coastal migratory whale imaging systems.

Discussion/recommendations

In this study, we collected 55.7 h of footage using both surface-based and airborne thermal imaging systems on a TBS to monitor gray whales, avian species, and other marine wildlife. This investigation represents a novel approach that significantly expands the limited dataset of TBS-based marine wildlife observations (Flamm and Kaufmann 2006; Flamm et al. 2007; Hodgson 2007; Adams et al. 2020) and demonstrates the capabilities of TBS for conducting marine wildlife observation. The key findings demonstrate distinct temporal patterns in species detection, with gray whales being most frequently observed from the surface between sunset and midnight, while human-processed airborne detections peaked in the mid-morning and early afternoon. An intercomparison of the Toyon algorithm and human processing revealed that an increased percentage of Toyon detections that human analysts did not detect occurred during daylight, indicating that sun artifacts may impair human image processing. The disparity between whale surface observations peaking from sunset to midnight and airborne human-processed observations peaking in mid-morning and early afternoon may also be attributed to increased imaging artifacts when the sun most impacted the airborne camera FOV near sunset. Avian species were observed both day and night, with peak sightings occurring around midday and in the early afternoon. Sea otters and harbor seals were primarily detected in the morning. Notably, whale detections were more successful at lower flight altitudes and higher camera

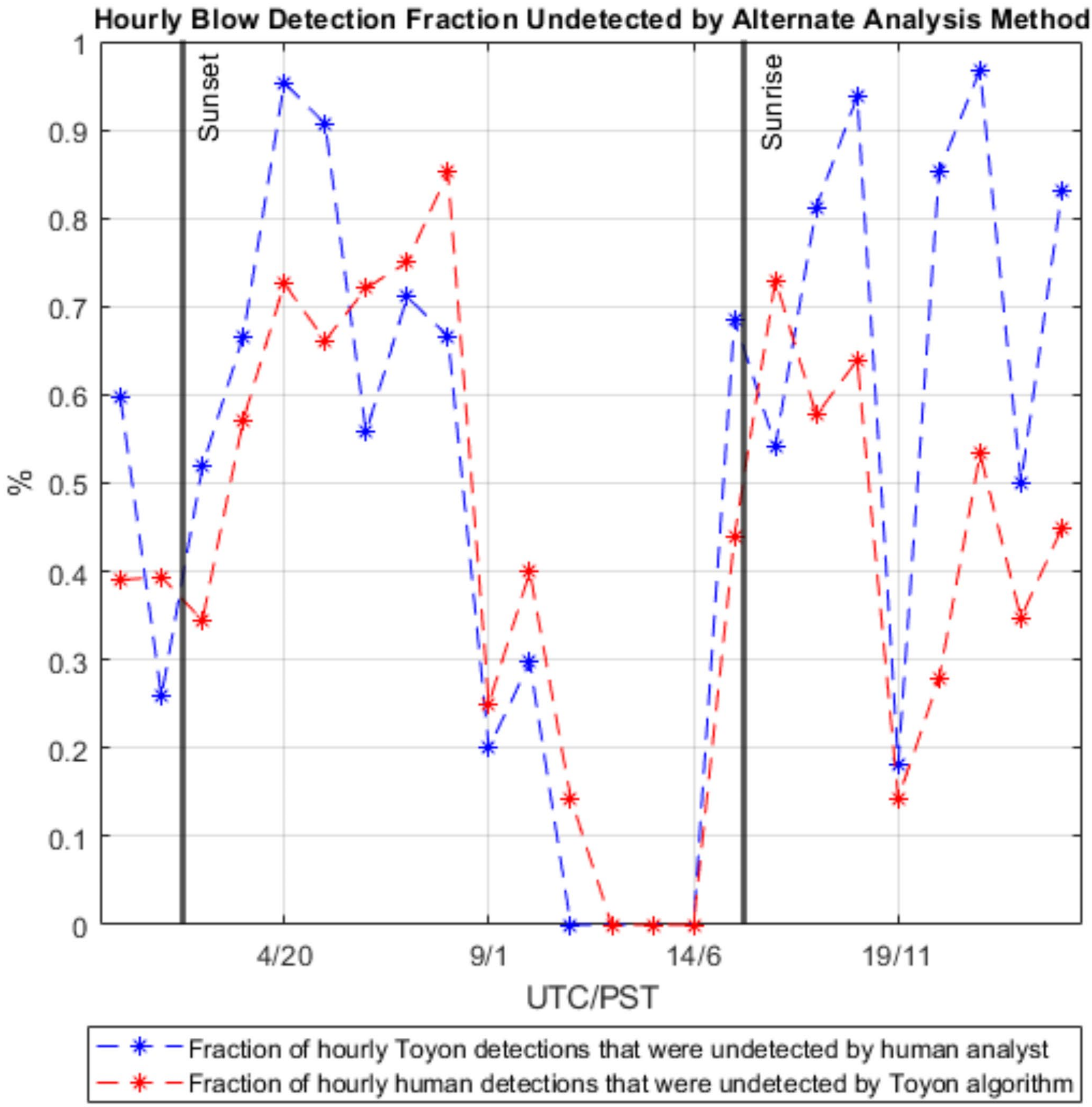

Fig. 17 Fraction of blow detections by hour from the surface 8640 camera that were not detected by the alternate detection method within 3 min

resolutions, suggesting that future monitoring may benefit from coastal towers or offshore structures equipped with thermal imaging systems. Additionally, this study highlights the differences in diurnal detection efficiency between human observers and the TBS, with implications for optimizing future wildlife monitoring efforts.

The comparison between surface-based and airborne observations revealed key insights into the efficacy of each method in detecting marine wildlife. Surface-based thermal imaging captured significantly more gray whale sightings in total than the airborne thermal imaging with the TBS because of the continuous nature of surface monitoring. However, the airborne TBS demonstrated unique advantages, particularly in detecting whales and avian species that were missed by surface cameras during simultaneous observations. For instance, 21% of airborne whale detections did not coincide with surface observations, indicating that the TBS can identify animals in areas or at distances beyond the surface sensor's FOV. These discrepancies suggest that a combination of both methodologies could enhance the overall detection capability, particularly in applications that require monitoring a large area or distance from the observation site. Additionally, the choice of scan patterns, flight altitudes, and imaging equipment significantly influenced detection rates, with variable-pitch scanning proving more effective for whale blow detection. Further refinement of these operational parameters will be critical for improving the accuracy and efficiency of wildlife monitoring in future studies.

To enhance the impact of this study, several recommendations for future research and practical applications emerge (Table 5). First, further investigations should focus on refining scanning methodologies, particularly the variable-pitch scan, which demonstrated the highest detection rates for whale blows. Automating this process could reduce operator fatigue and increase efficiency. Additionally, exploring the integration of ML algorithms for the real-time processing of airborne thermal imagery, that does not provide a constant background state, could streamline data analysis, allowing for quicker decision-making impacts from aerial wildlife monitoring. Given the success of lower-altitude observations, future studies should consider deploying

Table 5 To enhance the operational efficiency and scientific output of the TBS and imaging sensors for detecting and tracking marine wildlife, the following recommendations aim to advance the use of the TBS and imaging Sensor's capabilities for wildlife observation in marine environments

Optimization of Scan Patterns	
Variable- vs. Fixed-Pitch Scans	The variable-pitch scan exhibited a higher rate of whale blow detections, though it was more labor intensive and time consuming. Future efforts should explore automating the variable-pitch scan pattern to reduce operator fatigue and improve efficiency. Alternatively, reducing the number of scans to target the area of most frequent target detection could shorten the scan period from 135 min without significantly sacrificing detection rates.
Automated Loitering Patterns	Given the relatively low whale detection rate in the loitering pattern but its simplicity for automation, further research should be conducted on improving loitering pattern efficacy, particularly through the optimization of altitudes and camera angles.
Machine Learning and Real-Time Processing	
Improved AI Models for Whale and Avian Detection	While the Toyon ML algorithms were successful in detecting whale blows, continuous improvement in the AI models can be pursued by integrating more diverse datasets and enhancing the algorithms' ability to differentiate species (i.e., marine mammals and avian species). Future studies should evaluate real-time AI performance and its integration into flight operations.
Human vs. AI Processing	The study revealed limitations in manual human processing due to time, cost, and labor constraints. Implementing real-time ML detection systems could reduce the need for post-flight human analysis, speed up data review, and improve real-time decision-making during TBS operations. To make this transition, real-time ML detection costs will need to be comparable to the cost of manual human processing.
Environmental Conditions Impacting Detection	
Impact of Visibility and Atmospheric Conditions	Reduced visibility impaired the radiometric performance of the TBS's thermal imagers. Future studies should focus on developing or integrating sensors that can perform better under foggy or reduced visibility conditions, perhaps through multispectral or adaptive imaging technologies. Additionally, exploring atmospheric correction models to adjust imagery in real time could be valuable.
Lower- vs. Higher-Altitude Observations	As indicated by the higher detection rate at lower altitudes (50–100 m), future studies should consider deploying lower-altitude fixed monitoring platforms (e.g., coastal towers or offshore wind turbines) with thermal imaging systems. Comparative research on marine wildlife detection from both airborne and stationary systems would provide insights into the necessity of a TBS at certain altitudes.
Imaging and Detection Equipment	
Lens and Camera Comparison	The study showed that the 27 mm lens on the Mirage camera had better detection rates than the 11 mm lens. In future deployments, emphasis should be placed on using wider lenses like the 27 mm for wildlife detection. Further testing could explore a balance between resolution and FOV, especially to optimize the detection of different species.
Enhancement of Thermal Imaging Systems	The ICI Mirage 640 P MWIR camera is capable of increased detection performance in cold conditions compared to the 8640 LWIR camera, particularly for whale detection. Additional research into other camera systems or emerging technologies that enhance detection accuracy in diverse marine environments could greatly enhance marine mammal and avian surveys.
Data Collection and Workflow	
Extended Operational Hours	Given the diurnal variability in whale and seabird sightings, extending TBS flights to nighttime hours and early morning could help maximize the likelihood of detecting marine life. Using a combination of human visual observations and AI at night may also enhance detection.

Table 5 (continued)

Collaboration Between Human and Machine-Learning Observations	Comparing TBS detections with NOAA's human visual surveys has proven effective. More research should focus on how both methodologies can be better integrated, for example, by incorporating real-time NOAA observations as feedback to the TBS, allowing more accurate and targeted camera adjustments.
Long-Term Marine Wildlife Observation Programs	
Multiyear Campaigns	Repeating observation campaigns over multiple years would enhance the understanding of seasonal migration and the diurnal and interannual variation in population size and identify the long-term effects of environmental changes on marine wildlife. This approach would allow for comparisons between human and AI-based detection systems and for AI-based systems to become reliable in the detection of various species and possibly behavioral changes, which would be beneficial data for renewable energy development and regulatory agencies. A strategic, persistent implementation of the observational techniques in this study (surface, airborne, human observer) is required to understand reproductive success and survival as well as mortality or behavioral changes induced by human activities.
Strategic Siting	Positioning the TBS in areas with high marine biodiversity, key wildlife corridors, or regions undergoing significant ecological changes (e.g., offshore wind installations and offshore oil platforms) will maximize data collection and impact.
Multisensor Integration	Future efforts should incorporate additional sensors like acoustic monitoring for whales, water quality sensors, eDNA samplers, and multispectral satellite data to create a more comprehensive observation system for marine ecosystems.
Remote Sensing and Satellite Pairing for Long-Term Marine Wildlife Monitoring	Satellite technologies, such as NASA's Landsat, MODIS, and Sentinel, provide crucial data on ocean conditions and biological activity, aiding in the monitoring of marine ecosystems and wildlife. Combined with AI-based detection, these tools enable real-time tracking of migration, behavior, and population trends across vast areas. Remote sensing also helps monitor ecological changes and the impacts of human activities like offshore wind farms and oil platforms on wildlife. When paired with autonomous TBS sensors, these technologies create a comprehensive system for tracking long-term population trends, supporting ecological conservation efforts and minimizing environmental impact. It is recommended that this approach be incorporated into future studies to enhance marine wildlife monitoring and inform conservation strategies.
Continuous Offshore Monitoring	Deploying the TBS on offshore platforms—such as oil platforms, offshore wind towers, and buoys—enables continuous monitoring of wildlife and the environment, supporting long-term tracking of population trends and ecological changes. Future studies should focus on enhancing the autonomous operating capabilities of TBS in rugged offshore conditions to improve their effectiveness as long-term marine wildlife observation tools.
Offshore Wind and Marine Energy Monitoring	The TBS can monitor wildlife interactions with offshore wind developments, providing critical data on the ecological impact throughout the construction and operation phases (Courbis et al. 2024). Again, future efforts should optimize the autonomy and persistence of TBS in the offshore environment.
Sea Turtle Monitoring	While not included in the current study because the study area does not encompass sea turtles, the TBS is a valuable tool for monitoring them. It can assist in tracking migration routes, nesting sites, and interactions with offshore developments, thus contributing to conservation and regulatory efforts (Danovaro et al. 2024). Future studies in sea turtle habitats would be beneficial in indicating how TBS capabilities can inform conservation strategies, regulatory needs, and the installation of renewable energy sources with minimal or no impact on sea turtles.

stationary monitoring platforms, such as coastal towers, to complement aerial efforts, especially in high biodiversity areas. Moreover, the findings underscore the importance of collaboration between human observations and automated systems, suggesting that integrating NOAA's real-time human observer data could optimize monitoring strategies. Future studies should evaluate the efficacy of combining fixed observations from a TBS with mobile, ship-based TBS wildlife observations. This approach could optimize persistent monitoring over large areas while identifying target areas with a fixed TBS and use ship-based TBS for higher resolution, real-time observations in active corridors, allowing greater detail about individual animals and their health to be collected (Marvin et al. 2016; Horton et al. 2017; Nathan et al. 2022). In addition, TBS data, can be combined with satellite data from remote sensing technologies like NASA's Landsat, MODIS, and Sentinel to enhance real-time tracking of wildlife migrations, behavior, and habitat changes, providing a comprehensive understanding of marine wildlife interactions with their environment, especially in remote or expansive marine areas (Chassot et al. 2011; Pettorelli et al. 2018; Ayoola et al. 2024; McCauley et al. 2024). Ultimately, these advancements could inform conservation practices and regulatory frameworks, particularly in the context of emerging offshore developments, ensuring that wildlife protection remains a priority amid growing human activities in marine environments.

Conclusion

This study highlights the capabilities of the TBS and advanced imaging sensors in effectively detecting and tracking marine wildlife, primarily gray whales and avian species. Over the course of 55 h of flights, we gathered extensive data on marine biodiversity, demonstrating the potential of strategic flight patterns utilizing thermal imaging on TBS to conduct marine wildlife detection. This study significantly expands the pre-existing body of work concerning TBS-based wildlife studies and evaluates how TBS may be integrated with UAV and human observations, particularly with respect to conducting observations at night or in reduced visibility. The findings indicate that TBS operations at altitudes between 50 and 200 m are optimal for marine wildlife detection, with the variable-pitch scanning pattern emerging as the most effective method for identifying whale blows compared to fixed-pitch and loitering patterns. This suggests that adaptive scanning techniques with TBS can greatly improve our understanding of marine species' distribution, movement, and potential behavior.

The study revealed instances where airborne detections were not corroborated by surface observations, underscoring the complementary role of aerial monitoring to traditional survey methods. Furthermore, a comparative analysis of detection rates between the TBS and surface-based observations illustrates the strengths of aerial imaging technologies in identifying marine wildlife over a larger area. While ML algorithm image processing and human processing provided similar results in our study, the ML algorithm was more costly at this early stage of development. As ML algorithms are refined and cost decreases, they are on track to enhance wildlife image processing efficiency, paving the way for real-time monitoring capability from airborne platforms. A valuable insight from the ML algorithm was that 75.8% of blows were detected between 1 and 2.5 km from the surface camera, which informs design criteria for coastal migratory whale imaging systems.

The successful calibration and integration of diverse imaging sensors within the TBS framework further illustrate the potential for creating a comprehensive monitoring system that can adapt to environmental conditions, operational challenges, and observational goals. This research not only provides valuable insights into gray whale detections and population studies but also lays the groundwork for future studies in marine biodiversity monitoring, particularly from TBS, and particularly in relation to conservation strategies and the sustainable development of ME and offshore wind resources.

In conclusion, these findings underscore the critical importance of incorporating aerial surveillance technologies, advanced imaging sensors, and in situ methodologies in marine wildlife research. Such advancements facilitate a deeper understanding of species behavior while supporting effective conservation efforts. Future research should prioritize refining operational methodologies and advancing the autonomy and ruggedization of aerial platforms. Additionally, the applicability of TBS in different ecological contexts should be explored to enhance the capacity to observe marine ecosystems and wildlife, which is essential for the sustainable management of offshore wind developments and other ME initiatives.

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Data availability Data will be made available under the license CC-Attribution 4.0 via the Portal and Repository for Information on Marine Renewable Energy (PRIMRE) on the Marine and Hydrokinetic Data Repository (MHKDR) https://mhkdr.openei.org/, accessed on 31 December 2024].

Declarations

Conflict of interest The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Ethical compliance This study did not involve the sampling of animals, and therefore, no permits were required. We affirm that all applicable international, national, and institutional guidelines for the care and use of organisms have been adhered to. As such, specific permissions related to animal sampling do not apply. We are prepared to provide any relevant documentation upon request.

Regulatory compliance This study was conducted in full compliance with all applicable regulations, including obtaining the necessary permits from the Federal Aviation Administration (FAA) for aerial operations. We adhered to all FAA guidelines to ensure safe and responsible use of unmanned aerial systems during the research.

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