

Article

Circumventing Blind Angles and Disturbance: Evaluating UAS for Monitoring Cliff-Nesting Seabirds

Johan H. F. Castenschiold ^{1,*} , Mækir B. Gullbein ², Sjúrdur Hammer ² and Morten Frederiksen ¹ ¹ Department of Ecoscience, Aarhus University, Frederiksborgvej 399, 4000 Roskilde, Denmark; mfr@ecos.au.dk² The Faroese Environment Agency, Traðagøta 38, 160 Argir, Faroe Islands; mækir@live.dk (M.B.G.); sjurdurh@us.fo (S.H.)

* Correspondence: johanhfc@gmail.com

Highlights

What are the main findings?

- We investigate the applicability and effectiveness of drones for surveying cliff nesting seabirds, specifically northern fulmars in the Faroe Islands.
- We identify optimal survey distances to minimize disturbance, and optimal camera tilt angles to maximize bird visibility.

What are the implications of the main findings?

- Drone surveys of seabird cliffs can provide a major reduction in time for data collection and enable monitoring of otherwise inaccessible breeding sites.
- Standardized survey protocols can enhance reliability, repeatability, and data quality of future surveys.

Abstract

Unoccupied Aerial Systems (UASs) offer great potential for monitoring breeding colonial seabirds. However, survey flights need to be planned carefully to maximize detection of birds, allow for reliable counts, and minimize disturbance. In this study, we evaluated UAS-based monitoring for the most numerous seabird species in the Faroe Islands, the northern fulmar (*Fulmarus glacialis*), assessing both disturbance and optimal viewing angles. We found that behavioral disturbance could be minimized by adhering to a set of strict operating protocols, including strategic and flexible flight paths that ensured UAS distances remained above vigilance thresholds, allowing for initial habituation and limiting responses to the presence of the UAS. During surveys, quantifiable behavioral alterations (vigilance) were observed at distances ≤ 57.5 m in mixed areas containing both incubating and resting individuals, and ≤ 32.9 m in areas with only incubating individuals. At greater distances, only light responses (head turning) occurred. To optimize monitoring efficiency, we found that a slight downward camera tilt of -13.8° consistently provided the highest bird visibility, detecting 93% of individuals. Complete visibility was achieved by covering a range from -30° to -1.3° , depending on terrain type and bird age group, highlighting the observation angle as a critical factor for reliable surveys in the investigated complex topography. Overall, these results will provide a strong foundation for further research into tailored flight and survey protocols for cliff-nesting seabirds utilizing UAS technology.



Academic Editors: Humberto Perotto-Baldivieso and Aaron M. Foley

Received: 25 April 2026

Revised: 22 June 2026

Accepted: 24 June 2026

Published: 27 June 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons](https://creativecommons.org/licenses/by/4.0/)

[Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: behavioral alterations; observational angles; visibility simulations; spatiotemporal positioning; drone

1. Introduction

Seabird monitoring schemes targeting estimation of population size traditionally rely on direct visual observations, which require an unobstructed line-of-sight from the observation point to the target area [1]. Other, more recent methods include camera traps or manual photography of the nesting area [2]. However, there are several drawbacks to the traditional methods for monitoring seabird populations, especially when surveying complex environments characterizing many coastal breeding sites with steep coastlines and challenging topography and accessibility. At such sites, birds are often obstructed from view when observing from below, and access can pose a considerable safety risk for the surveyor [1] as well as a further risk of disturbing the birds [2,3].

Remote sensing is a fast-emerging discipline within wildlife monitoring, which may promise faster, more precise, and larger-scale data acquisition [4,5]. Importantly, such data are typically captured from above, thereby changing the perspective and offering a better observation angle. One such technology is Unoccupied Aerial Systems (UAS) equipped with still or video cameras [6]. This tool offers great potential for wildlife monitoring in general, and for monitoring of breeding colonial seabirds in particular. In recent years, UAS technology has advanced rapidly and is now regarded as a highly advantageous tool within several scientific disciplines [4]. In many cases, the use of UAS can contribute to an effective and rapid gathering of data, often offering new perspectives and insights. Yielding an unbiased spatial and temporal snapshot, the resulting UAS imaging will further be readily available for retrospective post-processing. The current range of camera UAS features a wide variety of sensor types, ranging from ordinary color imaging via infrared–thermal to LIDAR-scanning sensors [7], which further expands the potential applications of UAS in nature management and conservation. A growing number of studies are currently exploring the applications of UAS-based remote sensing technology for monitoring wildlife populations, particularly in remote and inaccessible habitats [3,5,8,9]. With increasing flight ranges due to advances in battery-powered propulsion systems, as well as onboard avoidance sensors allowing for terrain awareness, UAS surveys are now gaining a footing in Arctic areas, which are characterized by low accessibility and difficult terrain [3,10]. Consequently, there now seems to be great potential for UAS to assist in monitoring Arctic seabird populations nesting in challenging and rugged terrains, such as in the Faroe Islands.

The Faroe Islands, centrally located in the Northeast Atlantic, are dominated by steep, inaccessible, and complex sea-facing cliffs and sea stacks that in many places reach heights of several hundred meters [11]. These landscapes provide ideal nesting habitats for large populations of several seabird species [12,13], but their very nature poses significant logistical, economic, and observational challenges for monitoring efforts. Traditional ground-based survey methods and boat-based surveys are often impractical or unsafe due to the steepness, height, and remoteness of many nesting locations, limiting the effectiveness of visual counts and leaving large sections of breeding colonies uncounted or under-surveyed. In this context, UAS technology presents a transformative opportunity for seabird monitoring in the Faroe Islands. UAS equipped with high-resolution cameras can access and capture images of cliff faces and sea stacks from above or from the side, providing comprehensive coverage that would otherwise be impossible from the ground or the sea. This aerial perspective could allow researchers to survey entire colonies, including those located on narrow ledges or isolated stacks, with minimal disturbance to the birds and greatly reduced risk to observers [3,14]. Furthermore, the imagery collected can be archived and then analyzed in detail at a later stage, supporting more efficient data collection, more accurate population estimates, and facilitating long-term monitoring efforts. The adoption of UAS-based surveys is thus particularly well-suited to the Faroe Islands' rugged coastal

environment, offering new possibilities for effective, repeatable, and safe monitoring of seabird populations.

A key objective, however, is to avoid disturbance to the birds, both through the visual appearance and sound perception of the UAS, which is important for ethical reasons and to obtain reliable and unbiased results [3,15]. Disturbance to birds can be visually detectable and manifests as behavioral alterations or causes physiological alterations (e.g., elevated heart rate) [9]. Different seabird species may react differently to the presence of UASs, often according to colonial or solitary nesting traits and habitat preferences [3]. It is therefore often necessary to conduct specific studies to draw up suitable flight protocols that can be applied on a larger scale [6].

One species for which new monitoring approaches are urgently needed is the northern fulmar (*Fulmarus glacialis*; hereafter fulmar), a widely distributed seabird in the North Atlantic. In the Faroe Islands alone, several hundred thousand pairs are estimated to breed [13,16]. Fulmars are highly pelagic outside the breeding season, but nest in loose colonies on steep, rocky cliffs and offshore stacks. These habitats are sheltered and offer protection from predators, but pose major challenges for population monitoring [1]. The size of the breeding population has historically been difficult to assess, as traditional counting methods are generally unsuitable in these environments, both when observed from land and by boat in front of the cliffs [17]. During these types of surveys, large proportions of birds may remain invisible, obscured by ledges, rock protrusions, or vegetation. An improved knowledge of breeding site dynamics and the ability to monitor population trends can help us understand the fulmar's ecological importance and sensitivity to environmental changes, such as shifts in prey availability and exposure to pollutants [18,19]. During the last 10–20 years, a marked decline in the Northeast Atlantic fulmar population has been recorded [20], and this is also reported locally on a small island in the Faroes [17]. Innovative monitoring techniques are therefore essential to accurately assess the current and future size, fitness, and trends of fulmar populations, as well as to identify potential population stressors.

This study aims to explore and evaluate UAS as a tool for surveying cliff-nesting fulmars, specifically in the Faroe Islands, by: (i) developing and testing protocols that minimize disturbance through behavioral analysis and optimal flight parameters, (ii) determining the optimal observation angles for maximizing detectability and reliable identification of birds and nests under varying conditions, and (iii) assessing the suitability of these methods across different nesting environments, including different islands with different topography and geology. We seek to provide transferable insights for broader UAS-based applications for cliff-nesting fulmars and similar seabird species, thereby establishing practical and ethical guidelines for accurate monitoring of otherwise inaccessible seabird colonies.

2. Materials and Methods

2.1. Study Species

Fulmars breed widely in the Faroe Islands, forming loose colonies of variable size on cliffs, both along the coast and inland. Each pair lays a single egg in mid-to-late May, which is incubated for 48–53 days and hatches from late June to early July [16,21,22]. Fledging occurs in mid-to-late August. The remote and inaccessible nature of these breeding sites makes conventional population monitoring challenging. North Atlantic fulmar populations also face considerable hunting pressure, with annual harvests in the Faroes of around 100,000 birds [16] and with smaller numbers harvested in Iceland [23]. This highlights an urgent need for robust monitoring to inform conservation and management efforts.

2.2. Field Work and Survey Sites

Data were collected during three consecutive breeding seasons, 2021–2023, totaling 33 unique survey days from June to August. We conducted a total of 283 UAS survey repetitions, which comprised 203 observation angle recordings and 80 behavioral response recordings (Table S1). The fieldwork was distributed across 18 unique sites on 10 islands, with sites of varying character, including elevation above mean sea level (AMSL) and geological terrain. To accommodate for shifting environmental factors, such as vegetation height and fulmar breeding stage and behavior, we repeated the surveys throughout most of the season (Figure S1). The survey effort was distributed across June (84 survey repetitions), July (85), and August (114). Furthermore, to account for possible diurnal variation in behavior [24], all flights were conducted at varying times during the day. This sampling scheme was established to obtain temporal and spatial coverage of the study area during the breeding seasons.

Geographically, we designed the data collection to cover sites spanning the Faroese archipelago from the northern isles to Suðuroy in the south (Figure 1). These sites were chosen to cover the variable topography and cliff structure across the Faroes. This was both greatly helpful in developing more broadly applicable guidelines for UAS surveying in the Faroes and in further investigating seabird colonies in different geographical settings and densities. Survey sites were chosen to include coverage of areas with varying densities, from low to high, varying cliff structure, which influences the optimal viewing angle, and varying amounts and height of vegetation, changing over the season.

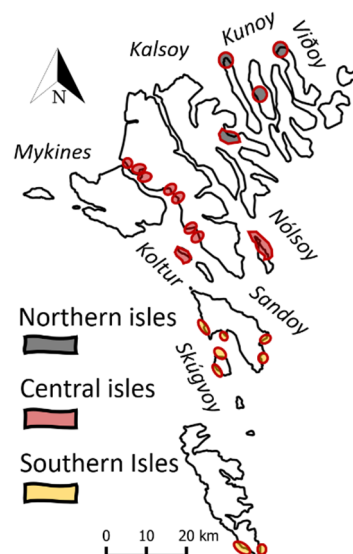


Figure 1. Graphical representation of survey sites with UAS flights in the Faroes during the survey seasons 2021–2023.

2.3. Survey Protocol

All data were collected using the DJI Matrice 300RTK quadcopter UAS platform equipped with the DJI H20T camera payload (DJI, Shenzhen, China), and flights were executed via the DJI Pilot 2 app (v2.5.1.3). The H20T features a 20-megapixel RGB camera with a 1/1.7" CMOS sensor, with an optical zoom capability of up to 23× with further digital zoom. The camera's built-in software for stabilizing and tracking was crucial for precise real-time targeting and maintaining continuous focus on regions of interest during the flight operations. Additionally, during flight, the onboard laser range finder (LRF) was used to continuously monitor the distance from the UAS to the target plot area with fulmars. Accurate distance measurement was critical for both behavioral interpretation and ensuring safe operation in the challenging cliff environment.

After launching the UAS in the vicinity of the survey site to allow time for habituation [3], we navigated the flight along the cliffside until a suitable area (min. 100 m²) with fulmars was spotted. The DJI pilot app's built-in "live track" functionality was then used to stabilize the view and maintain focus on the target individuals throughout the observation period. This smart capture functionality automatically kept the area of interest in focus by continuously adjusting the camera's orientation and zoom, ensuring that the selected region or subject remained centered and sharp even as the UAS maneuvers. Both video capturing and screen recording were initiated to document the flight, visibility, and responses in real time.

Once the view was stabilized, we maneuvered the UAS according to the flight's purpose, which included a coordinated and steady approach to document visual behavioral responses, as well as controlled vertical movements to record visible angles. Additionally, we maintained a perpendicular viewing angle in the horizontal plane to prevent birds from disappearing behind obstacles from the side. The range of angles was empirically tested in as diverse breeding habitats as possible. To maximize the accuracy and reproducibility of observations, metadata for all relevant parameters, including flight trajectory, altitude, camera angle, timestamp, LRF-based distance readings, and environmental conditions, were continuously recorded by the UAS system. These metadata were subsequently extracted from the onboard logs and video files, ensuring precise synchronization between behavioral data, visibility, and flight parameters for subsequent analyses.

2.4. Behavioral Response Protocol

Behavioral responses were recorded using a customized classification system, according to the degree of vigilance, which was inspired by findings and classifications in previous studies looking at primarily seabirds [3,8,9] and shorebirds [25]. Moreover, whenever possible, we differentiated between bird age groups and activity, i.e., between adults and chicks, and incubating and roosting/non-incubating individuals. The differentiation between incubating and non-incubating fulmars not linked to a nest was performed based on posture, where incubating birds were identified by their persistent low-profile posture, whereas non-incubating or resting fulmars were recognized by standing often with legs or feet visible, or occupying locations unsuitable for nesting or too close to established nests to represent a separate nest site [26].

2.4.1. Video-Based Analysis

Visual behavioral responses to the approaching UAS were analyzed from video material comprising short sequences (approximately 30 s to 1.5 min), which were sorted by both location (spatial) and date (temporal) for systematic review (Table S2). For each approach, we began the analysis by noting the LRF starting distance to the target cliff area and tracking the horizontal flight path towards the focal bird plot. Video recording continued until the UAS reached a distance of ≤ 7 m from the birds, or all individuals were seen as responding, at which point recording was stopped and the UAS was flown away from the survey plot. Once the UAS reached a distance of >150 m from the previous plot, a new plot was scouted and selected along the cliff, ensuring a minimum separation of 150 m before resuming the next recording and approach (Figure 2a).

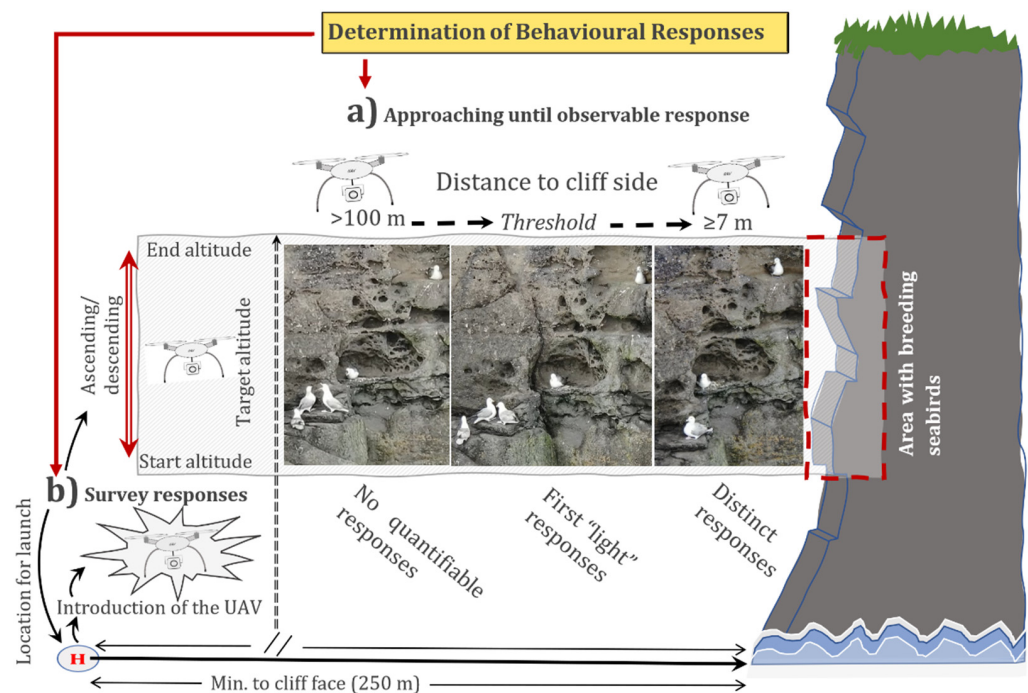


Figure 2. Graphical flowchart illustrating the protocol for evaluating behavioral responses of fulmars to UAS operations. (a) Responses provoked at the survey site during the UAS approach toward the cliff side, with distances to the breeding area indicated, and behavioral responses classified. The “threshold” denotes the distance at which the first quantifiable responses are observed in the birds. (b) Responses prompted during subsequent surveying by the introduction of the UAS into the survey area (soundscape), including survey responses observed after launch from a minimum distance to the cliff face. The flowchart highlights both the approach phase and the surveying phase.

During the video review, we recorded three distinct response levels (Figures 2 and S2). Firstly, light responses were attributed to head turning of the birds (LookUAS), and secondly, more pronounced and distinct responses were characterized as body movement of the birds (Vigilance) and moving away or disappearing (Flyoff). Furthermore, any potential influences of external factors were systematically recorded. These included flybys by other fulmars, which were recorded only when they provoked a response, as well as interactions with neighbors, which were classified into two distinct levels of interaction intensity. Additionally, we documented third-party interactions involving both conspecifics and the UAS to provide a better understanding of the behavioral context surrounding each observed response. In any given plot, the same bird was recorded only once for the same response, but could have multiple types of responses, which were recorded, but were still counted as a single individual overall.

To ensure consistency and efficiency, one observer performed all analyses of behavioral responses in regular conferences with the other authors and with a sample set functioning as a baseline of at least five images displaying each of the target response classes (Figure S2).

2.4.2. Observer-Based Analysis

In addition to the response flights outlined above, all behavioral responses (flybys) observable at a distance were systematically recorded during subsequent survey flights by a co-observer equipped with binoculars (Zeiss Victory 10 × 42, Zeiss, Oberkochen, Germany) or a spotting scope (Leica Televid 77, Leica Camera AG, Wetzlar, Germany), positioned alongside the UAS operator (Figure 2b). From launch through the start of each survey, every visibly appearing and approaching flyby of fulmars was documented, with particular attention given to the duration of each flyby and any repeated occurrences. Furthermore,

the proximity sensor on the UAS was used to document any flybys <10 m from the UAS. These observations were compared to the total estimated number of individuals present in the survey area and within 100 m from the UAS, which enabled calculation of the fraction of birds responding. Additional parameters noted included the duration of each response and whether responses were repeated by the same individuals, which helped provide a more nuanced understanding of behavioral patterns related to UAS presence.

Moreover, throughout this process, we recorded weather conditions, including wind speed, temperature, cloud cover (using the octa scale), and precipitation, to investigate how these factors influenced both fulmar behavior and the effectiveness of the UAS operations. These data were derived from nearby weather stations and weather cameras [27].

2.5. Measurements of Optimal Observation Angles

Having established guidelines for surveying with minimal disturbance, the determination of optimal observation angles was essential for conducting reliable surveys in challenging terrains, such as uneven cliff sides with grass-covered shelves with suboptimal angles risking rapid loss of sight of individuals (Figure 3). The use of UAS made it possible to empirically test and determine the optimal range of observation angles in diverse breeding habitats, which are highly dependent on specific locations, varying cliff structures, and, additionally, on seasonal variations in vegetation height (Figure 3a). We conducted dedicated UAS flights with the built-in “live track” functionality to stabilize the camera view of the survey plot and recorded video material for line-of-sight analysis. During the surveys, all plots were tested in the angle range of $+38.5^\circ$ to -88.9° camera tilt by flying the drone in a continuous movement vertically up and down the cliff side. This secured a close approximation to the total number of birds present.

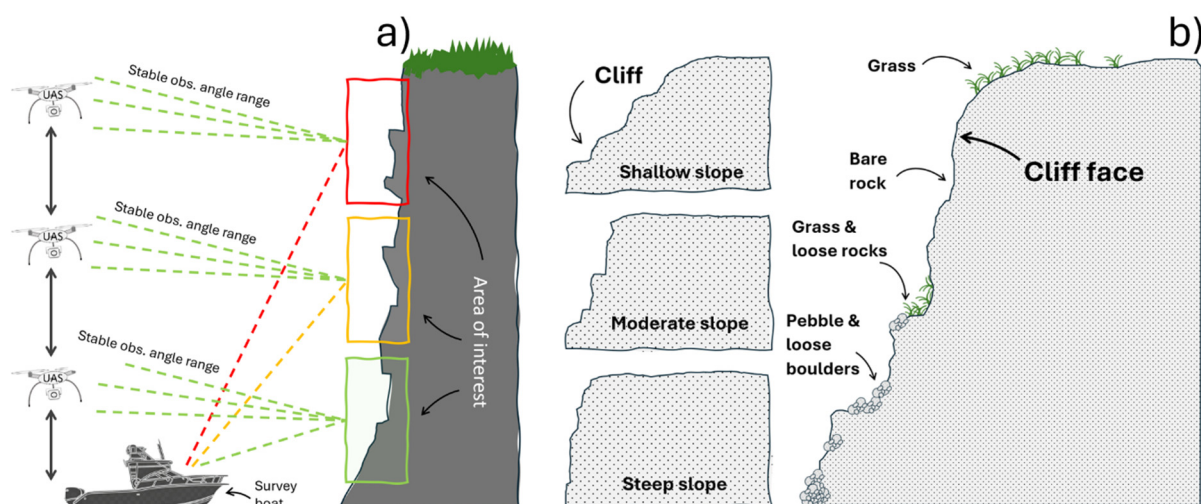


Figure 3. Graphical comparison of traditional (boat/ground) and UAS-based counting approaches at a seabird cliff colony. (a) UAS enables stable observation angle ranges towards the target area, in contrast to traditional methods, where only a limited and fixed range is obtainable and often from far below the target area. The vertical gradient of potentially overlooked birds can thus be determined with greater precision. (b) Illustration of the used site characterization based on cliff face terrain features, with annotation of vegetation, slope, and erosion, each classified into three levels (low, moderate, high).

2.5.1. Differentiating for Site Characteristics

To enable a more nuanced evaluation of possible environmental factors that could influence the measured observation angles, we noted relevant site characteristics. These characteristics were grouped into three categories according to terrain type, vegetation,

slope, and erosion, each with three levels: low, moderate, and high (Figure 3b). The classification was based on appropriate criteria (Table S3 & Figure S3).

2.5.2. Video-Based Line-of-Sight Analysis

All video sequences were systematically sorted and grouped according to site, location, date, and time of day (Table S4). For each sequence, relevant recorded metadata, including camera viewing pitch, “gimbal pitch”, and absolute altitude, was synchronized and displayed as subtitles (SRT files) in the VLC media player (v3.0.20, VideoLAN Organization, Paris, France), which enabled precise, frame-by-frame assessment of key parameters directly alongside video playback. Survey plots were sometimes divided across two video sequences, which were denoted as connected sequences (C-sequences).

Visibility events were annotated as soon as any individual fulmar became non-visible in the video frame. The criterion for visibility was standardized so that any bird with at least 5% of its body visible was considered “visible,” ensuring identification could reliably be made at this threshold, while birds with less than 5% body visibility were noted as “not visible” (Figure S3). This threshold of greater than 5% was maintained for consistency and reproducibility across observations.

Each video file was systematically reviewed to identify usable sequences in which at least one fulmar changed visibility behind the cliff while the UAS changed altitude. For every plot sequence, we logged detailed metadata for every visibility event. These metadata included location, sequence and sub-sequence ID, continuity with previous sequences, presence of non-fulmar species, total number of fulmars consistently present throughout the video (whether visible or hidden), activity state (incubating or resting), presence of chicks, slope steepness (categorized as shallow, moderate, or steep), vegetation type (bare rock, grass and rock, or grass), erosion level (low, moderate, or high), and the altitude at horizontal gimbal plane (pitch = 0). We annotated visibility events by either playing the video in real time or advancing it in 3–10 s intervals. Whenever in this process one or more fulmars disappeared, defined by the 5% visibility rule, the video was paused, and key details were noted, including the number of birds disappearing (within approximately 1–3 s and a ~5 degree range), timestamp, UAS direction (upwards or downwards), and the gimbal pitch at the time of the event. Following the disappearance of the last fulmar, we recorded the minimum gimbal pitch for downward hovering, and the same procedure was repeated for upward hovering. Each survey plot was then assessed in sequence for both orientations: above horizontal (upwards) and below horizontal (downwards).

2.6. Data Analysis

All analysis was performed using R (v4.5.2) [28].

2.6.1. Analyzing Behavioral Responses

Responses from the recorded video material from the UAS flights were quantified as the fraction of observed responses among individuals in each investigated plot. For each behavioral class, if no response was observed in a video clip for a given plot, a value of zero was assigned at the closest measured distance. Additionally, a value of zero was assigned at the start distance for each class in every plot where no responses were detected, ensuring that the absence of response was systematically recorded across the surveyed range.

To analyze behavioral responses to UAS proximity, we conducted a segmented regression analysis using shape-constrained additive models (SCAM) to fit monotonic decreasing curves to behavioral alteration data across different distances [29]. This approach was inspired by a previous study [30] and performed using the Segmented package in R [31]. For each unique combination of behavioral class and activity (i.e., LookUAS, Vigilance, Flyoff, and Resting vs. Incubating), we grouped the data and fitted a strictly decreasing smooth

function to the proportion of individuals displaying behavioral alteration as a function of distance from the UAS. Curve flexibility (number of base functions) was adjusted for the specific behavioral classes to prevent overfitting. Predicted response curves were generated at high resolution, and elbow points, representing the distance at which behavioral response changed most rapidly from a “flatline”, were identified using maximum curvature detection, threshold-based drop analysis, and a position-based fallback method (Figure 4a). Parameters were optimized to minimize the detection of spurious elbows near the origin and to ensure biological relevance. The formula can be denoted as follows:

$$d_i = \frac{|(y_n - y_1)x_i - (x_n - x_1)y_i + x_n y_1 - y_n x_1|}{\sqrt{(y_n - y_1)^2 + (x_n - x_1)^2}}$$

where (x_1, y_1) = the coordinates of the first point on the curve, (x_n, y_n) = coordinates of the last point on the curve, (x_i, y_i) = coordinates of the current point (i), and (d_i) = perpendicular distance from point (i) to the baseline. Then the elbow point is at (i^*) where (d_i) is maximized:

$$Elbow(i^*) = \arg \max_i d_i$$

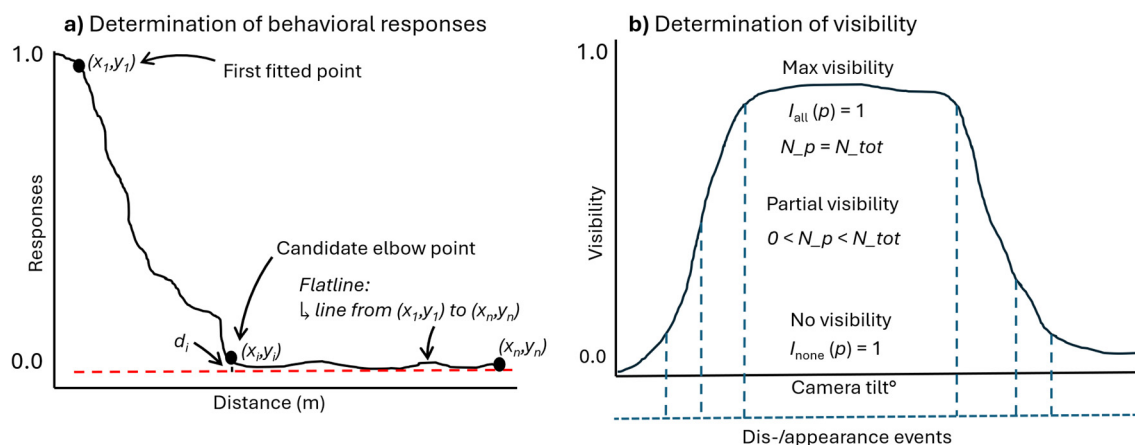


Figure 4. Schematic overview of the analytical framework used to identify behavioral-response thresholds and optimal camera pitch. (a) The elbow point was identified from the fitted monotonic response curve as the point with the last distinct shift in perpendicular distance (d_i) from the flat-/baseline connecting the first and last fitted values. (b) Visibility was interpolated across camera tilt angles using appearance and disappearance events, distinguishing tilt ranges of full, partial, and no visibility for each surveyed breeding plot. The dashed lines indicate different levels of visibility.

Groups with insufficient data were excluded from curve fitting, and all results were designated by activity to allow direct comparison of behavioral patterns across contexts. The analysis was implemented using the SCAM and ggplot2 packages in R [32], with diagnostic outputs provided for both detected and missing elbow points, facilitating parameter adjustment and model transparency.

Responses observed in real time with binoculars during subsequent UAS flights were analyzed statistically to evaluate associations with environmental variables. Spearman’s rank correlation was used due to its robustness to non-normal and non-linear data distribution [33]. Where relevant, linear regressions and summary distributions were also calculated.

2.6.2. Analyzing the Optimal Tilt Range

During the video annotation, all bird appearance and disappearance events were recorded. This included the number of individuals affected, the total number of birds

present, and the minimum and maximum camera tilt angles for each sequence. To address gaps in the video sequence between extreme angles and observed events, visibility was interpolated across a fine grid of pitch angles (0.1° increments).

For each sequence, pitch angles within the range where all individuals remained continuously visible were assigned 100% visibility, representing the optimal detection region. Pitch bins beyond the last appearance or disappearance event, where all individuals were recorded as no longer visible, were assigned 0% visibility, indicating no detection opportunity at these angles. Transitional bins in between were assigned partial visibility based on the cumulative number of individuals present at each pitch angle. Visibility for each pitch bin p was calculated as follows:

$$\text{Visible}(p) = 100 \times \left[I_{\text{all}}(p) + 0 \cdot I_{\text{none}}(p) + (1 - I_{\text{all}}(p) - I_{\text{none}}(p)) \cdot \frac{N_p}{N_{\text{tot}}} \right]$$

where $I_{\text{all}}(p)$ and $I_{\text{none}}(p)$ indicate that respectively all or no individuals are visible, N_p is the number visible at pitch p , and N_{tot} is the total number present. The term $0 \cdot I_{\text{none}}(p)$ explicitly handles any theoretical cases when no individuals are visible, ensuring the formula returns zero in this scenario.

This approach enabled us to differentiate between the fully visible interval (100% detection), the fully obscured interval (0% detection), and transitional intervals reflecting partial visibility, allowing for systematic comparison across the full range of annotated camera tilts (Figure 4b). Data were subsequently optimized by spatial density, limiting the number of interpolated pitches to 50 points in between any two visibility events per sequence and 5 observations per pitch degree (Figure S8). Furthermore, each plot sequence was weighted according to the total number of birds present, ensuring that visibility estimates reflected the relative sample size.

Bird visibility as a function of tilt and site characteristics was modelled using Generalized Additive Models (GAM) with random effects, chosen for its flexibility and higher sensitivity to, e.g., quadratic effects [34], with a complementary log-log link and binomial error distribution, including random effects and smooth terms for pitch and terrain [35]. The GAM was specified as:

$$\text{logit}(\mu_{ij}) = s(\text{Pitch}_{ij}, \text{by} = \text{TypeTerrain}_i, \text{bs} = "tp", k = 5) + s(\text{TypeTerrain}_i, \text{bs} = "re")$$

where μ_{ij} is the expected probability of visibility for observation j within terrain type i , $s(\text{Pitch}_{ij}, \text{by} = \text{TypeTerrain}_i, \text{bs} = "tp", k = 5)$ is a smooth function of pitch for observation j in terrain type i fitted independently per terrain type using thin plate regression splines with 5 basis functions, and $s(\text{TypeTerrain}_i, \text{bs} = "re")$ is a random effect smooth for terrain type i , accounting for the hierarchical structure in the data. The model was fitted using a binomial family with a "logit" link to address asymmetric detection probabilities.

A full-visibility pitch interval for each group around the located optima was determined by identifying the minimal range of camera tilt angles (pitch) required so that every visibility plot sequence within the group included at least one instance of 100% visibility. If a sequence did not reach 100% visibility at any pitch angle, the highest observed visibility within that sequence was used instead.

In addition to analyzing terrain site characteristics, we assessed the influence of geographical island location on bird visibility. Again, Binomial GAM regression models with random effect for Island were fitted to evaluate how island-specific factors impacted visibility, accounting for variation across sequences and sites. We performed Mann–Whitney U-tests to enable robust comparison of median visibility rates between groups of islands, re-

ardless of distribution shape, thus providing complementary evidence for any significant island-dependent differences.

Lastly, we assessed the relationship between survey altitude and optimal camera pitch by calculating the pitch angle corresponding to maximum bird visibility for each sequence. For each survey plot and the corresponding survey, c (ASL) was recorded for each plot. A linear regression model was then fitted with pitch at maximum visibility as the response variable and height as the predictor variable, and the Pearson correlation coefficient (r^2) was calculated to quantify the strength of the correlation.

3. Results

3.1. Behavioral Responses

Analysis of the recorded footage of fulmars while approaching the UAS revealed that fulmar behavioral responses to UAS proximity were non-quantifiable and random at flight distances greater than 128 m for both incubating and resting birds (Figure 5). The first measurable response, identified as the detected elbow points and marking the onset of LookUAS behavior, occurred at 112 m for incubating, 107 m for mixed groups of incubating and resting individuals, and 128 m for plots with only resting birds. However, at these distances, fewer than 10% of birds showed a LookUAS response.

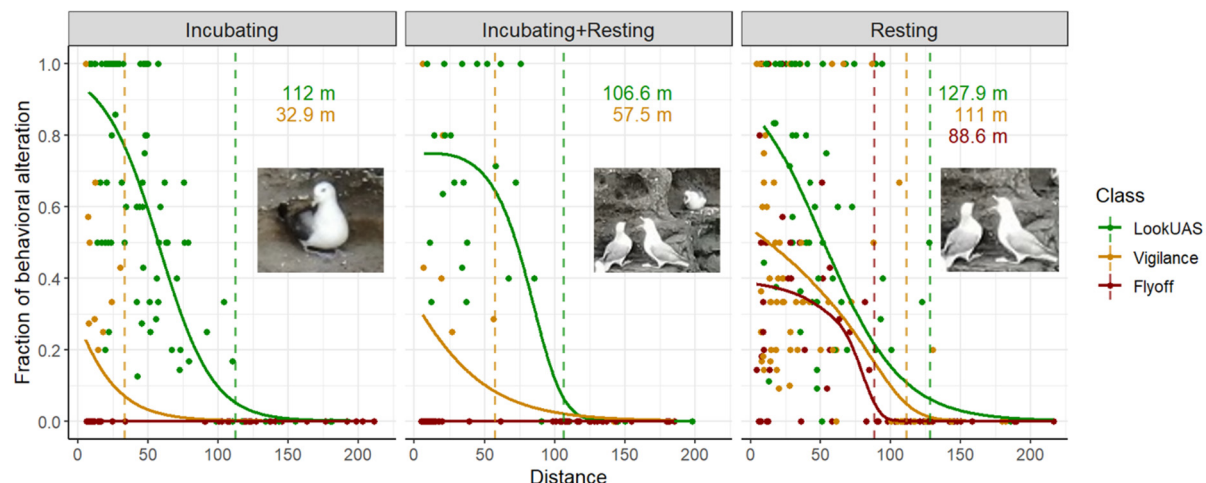


Figure 5. Behavioral alteration responses of fulmars to UAS proximity across activity groups. Points show observed behavioral alteration frequencies per plot sequence, with fitted monotonic binomial regression curves for each group: LookUAS (green, orientation toward the UAS), Vigilance (orange, heightened alertness), and Flyoff (red, flight). Each panel shows the responses across plots containing individuals of the three activity groups: Incubating, Incubating+Resting, and Resting. Dashed vertical lines indicate elbow points where responses first change rapidly and consistently. Elbow distances for LookUAS, vigilance, and flyoff responses are annotated for each activity group. Curves are fitted using shape-constrained additive models, ensuring monotonic increasing relationships.

Vigilance behavior was observed at shorter distances, occurring at 32.9 m for incubating birds and at 57.5 m for mixed groups, while resting-only plots showed vigilance at 111 m. Flyoff responses, characterized by birds taking flight, were only observed in plots that included non-incubating individuals, and no flyoff events were recorded in plots with incubating birds. While the individuals in survey plots with incubating fulmars exhibited LookUAS responses from 112 m, they topped out at only approximately 20% Vigilance, and no Flyoff responses occurred. In contrast, non-breeding individuals, in resting and mixed plots, exhibited higher rates of vigilance and flight responses. These differences in vigilance and flight between incubating and non-breeding states were clearly visible in the footage and quantifiable in the response curves (Figure 5).

Overall, the fulmars exhibited a hierarchical and graded sensitivity to UAS proximity across all activity groups, with LookUAS responses occurring at the greatest distances, vigilance at intermediate distances, and flyoff responses at the shortest distances and only for plots with resting individuals (Figure 5). This pattern was robust across activity groups (Figure S5).

In addition to the dedicated response surveys, we performed an analysis of observed fulmar flyby responses (fulmars flying towards the UAS) during subsequent UAS survey flights ($n = 279$). All these flights were conducted at the identified minimum distances (57.5 m). This analysis revealed that weather conditions, particularly wind speed, had a significant impact on fulmar flyby responses (Figure 6). fulmar flybys occurred in 49.8% of the cases, with repeated responses observed in 24.4% of flights and a mean response duration of 32.8 s. Close flybys within 10 m of the UAS were rare, occurring with only 4% of the total individuals. Both the duration and frequency of responses increased with higher wind speeds, supported by strong and significant Spearman correlations (duration: $\rho = 0.78$, $p < 0.001$; repetitions: $\rho = 0.486$, $p < 0.001$; Figure 6a,b).

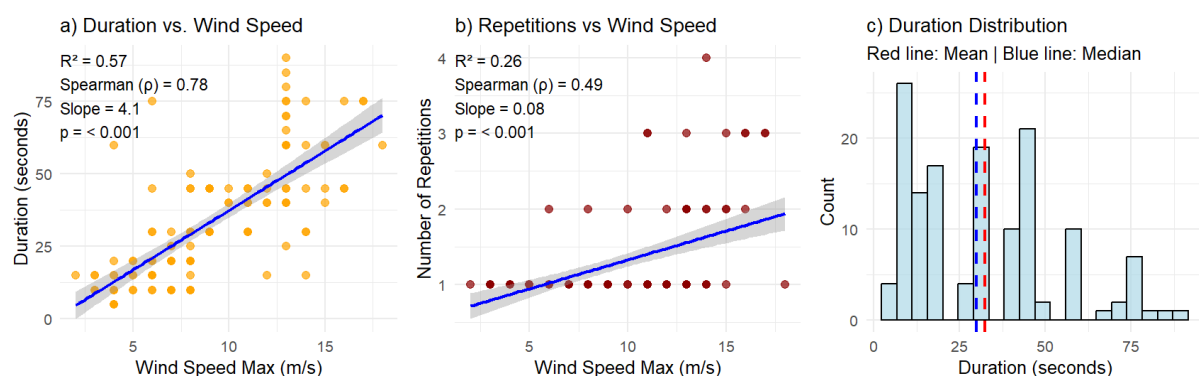


Figure 6. Weather effects on northern fulmar behavioral responses during UAS encounters. (a) displays response duration vs. wind speed, (b) repetition frequency of responses from the same individuals vs. wind speed (left), and (c) duration distribution for responses > 0 s. Scatter points each represent individual observations, with colored lines showing fitted trends with 95% confidence intervals. Statistical parameters and significance values are displayed for each relationship (flights ($n = 279$), 2021–2023).

Additionally, correlations were found between wind speed, cloud cover, and flyby rates out of the total number of birds present at the survey site. Here, the association between cloud cover and the probability for response reached statistical significance (Spearman (ρ) = -0.134 , $p = 0.025$, slope = -0.03 ; Figure S6a). This means that more overcast weather prompts a lower chance of response. In comparison, the associations between wind speed and the percentage of responding individuals were weaker and only significant for the occurrence of any individual birds (Spearman (ρ) = 0.125 , $p = 0.047$, slope = 0.029 , Figure S6b), whereas the response percentage of total number were non-significant (Spearman (ρ) = 0.109 , $p > 0.07$, slope = 0.08 , Figure S6c).

3.2. Optimal Observation Angle

We investigated a broad spectrum of camera pitch angles, ranging from -88.9° (downward) to 38.5° (upward). The results demonstrate that the disappearance direction is strongly associated with viewing angle (Figure S7). Specifically, for downward disappearance (Dir = D), the median pitch angle was 14.9° (interquartile range [IQR]: 6.6° to 22.9° , IQR = 16.3° , $n = 638$), while for upward disappearance (Dir = U), the median was -60.9° (IQR: -74.3° to -36.7° , IQR = 37.6° , $n = 432$).

Modelling using binomial generalized additive mixed models (GAMMs) allowed us to identify the range of camera tilt angles needed to achieve approximately 100% visibility. Across all groups, this optimal range spanned from -30° to -1.3° , with peak detection consistently observed around -13.8° with a 92% detection rate. Maintaining camera tilt within this optimal interval ensured maximal detection of birds across sites (Figure S8).

Mixed effect models that incorporated random effects of pitch for different environmental classes revealed significant variation in detection rates, highlighting the interactive effects of terrain and camera tilt on visibility outcomes (Table 1 and Table S5). Notably, the estimated optimal pitch angle for BareRock terrain was 8.65° higher than for GrassRock ($p = 0.013$), and 13.97° higher than for Grass ($p < 0.001$). Steep ledge sites exhibited an optimal pitch angle 2.66° greater than moderate ledge sites ($p = 0.032$), while high erosion environments had an optimal pitch angle 4.66° greater than medium erosion areas ($p = 0.013$). Among activity groups, the optimal pitch angle for adults was 5.32° higher than for chicks ($p = 0.008$). Other pairwise comparisons did not reach statistical significance. Overall, the results indicated that terrain type, erosion level, and age group are key determinants of optimal camera tilt for maximizing visibility (Figure 7).

Table 1. Binomial generalized additive mixed model (GAMM) with a random effect for site characteristics and age, fitted for peak visibility of independent analyzed plots and intervals with interpolated 100% visibility. For each grouping, the number of analyzed plots (Plots (n)) is listed, alongside the tilt angle at peak visibility (Peak visibility tilt $^{\circ}$) and its corresponding peak visibility (%). The “Range to cover for full visibility (100%)” columns indicate the lower and upper tilt angle boundaries within which full visibility is achieved for each grouping.

	Grouping	Plots (n)	Tilt with Peak Visibility		Range to Cover for Full Visibility (100%)	
			Peak Visibility Tilt $^{\circ}$	Peak Visibility %	Lower Tilt $^{\circ}$ Range	Upper Tilt $^{\circ}$ Range
Vegetation	BareRock	29	-6.3	92	-19.9	-6.2
	GrassRock	155	-15.6	92	-20.0	-6.9
	Grass	12	-21.2	87	-30.0	-15.7
Slope	Steep ledge	113	-13.0	93	-16.0	-1.3
	Moderate ledge	75	-15.3	90	-20.0	-8.0
	Shallow ledge	7	-15.6	88	-30.0	25.7
Erosion	High erosion	66	-11.10	94	-19.3	-13.3
	Moderate erosion	133	-15.3	92	-20.0	-5.8
	Low erosion	16	-20.1	90	-26.0	-6.2
Age group	Adult	111	-11.1	93	-25.4	-3.6
	Adult + Chick	16	-13.2	92	-30.0	-1.3
	Chick	58	-13.7	94	-18.0	-5.8

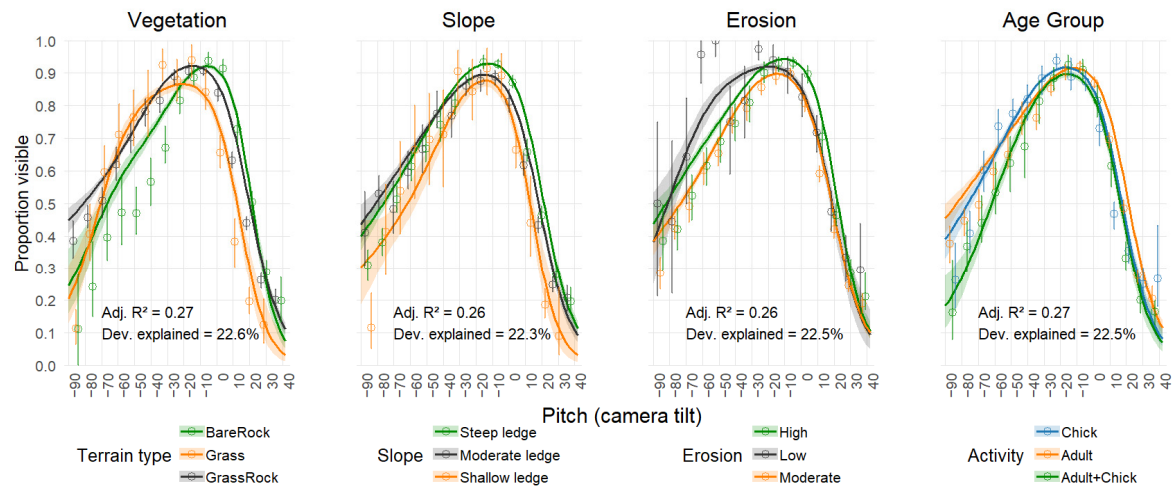


Figure 7. Detection proportions for a single viewing angle across Vegetation, Slope, Erosion, and Activity categories as functions of camera pitch angle (camera tilt). Solid lines represent fitted curves from a generalized additive model (GAM) with a binomial response, using a thin plate regression spline basis ($k = 5$), and shaded regions indicate 95% confidence intervals for the model predictions. Hollow circles show binned detection data with bootstrapped confidence intervals (error bars). Adjusted R^2 and deviance explained are reported for each category.

Analysis revealed a moderate positive linear correlation between site elevation and the optimal pitch angle for maximum visibility (Pearson, $R^2 = 0.13$, slope = 0.04, $p < 0.001$; Figure 8a), indicating that higher survey sites required slightly less downward camera tilt to maximize detection of cliff-nesting birds.

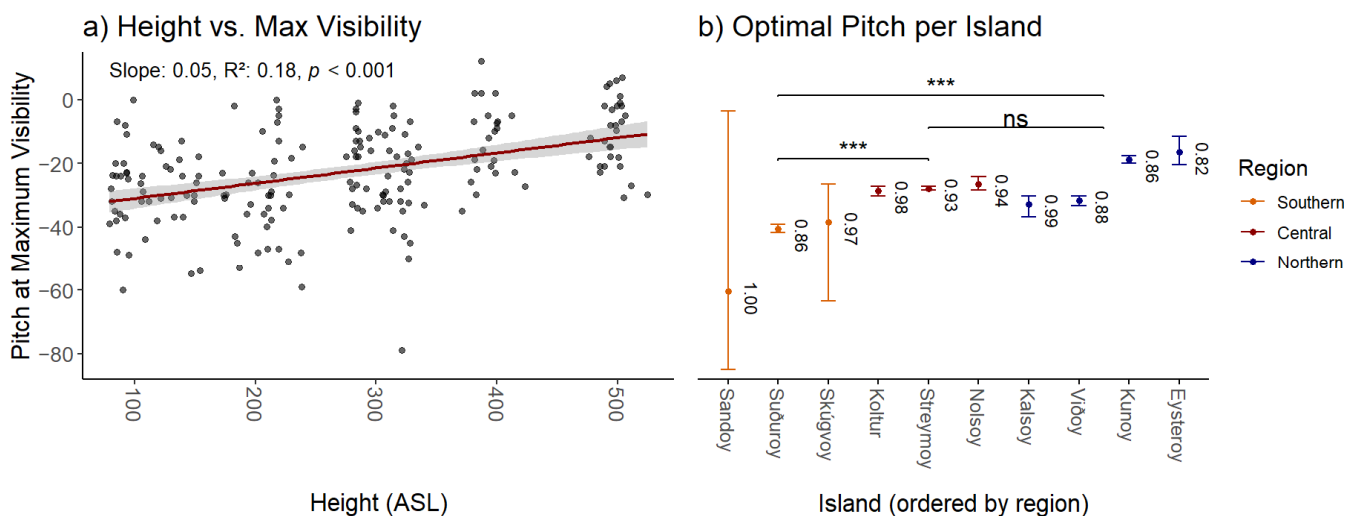


Figure 8. Relationship between survey altitude (ASL) and pitch at maximum visibility. (a) Scatterplot showing the relationship between plot height above sea level (ASL) and pitch angle at maximum visibility. Each point represents an individual plot; the red regression line and shaded 95% confidence band indicate a positive correlation (Pearson, $R^2 = 0.13$, slope = 0.04), suggesting that higher elevations require steeper camera tilts for optimal detection. (b) Predicted optimal pitch angle per island ($\pm$ parametric confidence intervals) from a binomial GAMM, with points colored by region (Southern: orange, Central: red, Northern: blue). Numbers above each point show predicted maximum visibility at the optimum angle. Horizontal brackets indicate pairwise Mann–Whitney U test results between regions (***) $p < 0.001$ and ns = not significant).

Furthermore, the optimal pitch angle varied notably among islands (Figure S9). Southern and central islands with higher erosion and more pronounced ledges, such as Sandoy, Suðuroy, and Skúgvoy, required the steepest tilts, whereas northern islands, with

lower erosion, including Viðoy and Eysturoy, exhibited more moderate optimal tilt angles (Figure 8b). Statistical comparisons confirmed significant differences in optimal pitch angles between southern/central and northern regions (pairwise Mann–Whitney U test, $p < 0.001$). In contrast, differences among northern islands were not significant. Lastly, a comparison between the seasonal time of the survey and camera tilt did not yield any significance.

4. Discussion

In this study, we highlighted the importance of a multi-phased approach for exploring and validating UAS as an advanced surveying tool for cliff-nesting seabirds, with a focus on the fulmar population in the Faroe Islands. Through careful consideration of the investigated parameters regarding behavioral alterations and robust data quality through optimized bird visibility, we developed a survey workflow that enabled monitoring with UAS along cliff sides with breeding fulmars. We were able to optimize survey efficiency and minimize disturbance to the surveyed birds, establishing a foundation for reliable UAS-based monitoring in challenging environments. Our results fit into the current expansion of studies on UAS as a promising assisting tool in the field of ecology and conservation [3,5,8,36].

4.1. Minimizing Behavioral Responses

The identified threshold distances for bird-to-UAS interactions of 32.9 m for incubating fulmars and 57.5 m for non-incubating, based on the onset of vigilant behavior, show that UAS surveys conducted above these distances were possible, while maintaining high image quality and ground sample distances (GSD) for most current UAS platforms and cameras, and while effectively minimizing disturbance. Notably, vigilance remained generally low across all distances, with below 25% of the incubating fulmars exhibiting vigilant behavior even at close range (approx. 10 m). These thresholds were determined using elbow points on fitted regression segments, a method that provided conservative yet robust estimates by pinpointing the first consistent change from baseline behavior [29,37].

It should be noted that the differences in Vigilance and Flyoff between incubating and non-breeding individuals may be attributed to the individual's affinity to and investment in the nest site. Consequently, incubating birds might exhibit less visible behavioral alteration while still being disturbed, metabolically, or otherwise. As such, flight protocols may benefit from adhering to the threshold distance for bird-to-UAS interactions for non-incubating individuals or mixed groups, thus applying a minimum flying distance of 57.5 m to the birds.

Our results correspond with previous research evaluating UAS disturbance for black-legged kittiwakes (*Rissa tridactyla*; [8]). Here, flushing was reported for nest-attending individuals to a flyby UAS at 30 m, and non-attending individuals were observed flushing at 60 m flybys. These results are close to our threshold finding for vigilance. Similarly, for Sub-Antarctic skua (*Stercorarius antarcticus*), distances of approximately 50 m are reported [9]. In contrast, our results showed markedly higher distances compared to gulls (*Larus* spp.), where a study [38] reported distances of 40 m for habituation and 15 m for active surveying, which prompted no visible responses. Our distances are also markedly higher than for both penguins (*Eudyptes* spp.), and giant petrels (*Macronectes* spp.) Here, a study [9] reported the first visual disturbance at an altitude of 25–10 m for both species groups. However, our study is unique in that we measured distances directly along the line of sight between the UAS and the target birds, rather than the more commonly used altitudinal height. This approach was necessary due to the vertical nature of our survey habitat. Consequently, direct comparisons to previous findings should be made with caution, as our results differ from most other studies by quantifying horizontal rather than vertical (altitudinal)

distance. The closest methodological approach is found in a study from Alaska, where some preplanned flights were performed along the surveyed cliff sides.

Our analysis of fulmar flyby responses during UAS surveys demonstrates that environmental conditions, such as wind speed, substantially influence both the frequency and duration of behavioral reactions. Higher wind speeds resulted in prolonged and more frequent flybys, while close approaches within 10 m remained rare (Figure 8a). These findings align with previous research showing that weather factors modulate seabird responsiveness to UAS [9,39]. Furthermore, increased cloud cover was associated with reduced behavioral response, suggesting that overcast conditions may help mitigate disturbance, possibly by camouflaging the UAS against the sky, making it difficult to see and detect for the birds, which is also pointed out by other studies [40] as a reduced tendency to flight under overcast conditions. Unlike for some species, e.g., Eurasian Oystercatcher *Haematopus ostralegus*, where surveying with UAS can lead to aggressive behavior [41,42], our results indicate that fulmars generally maintain a cautious distance, with only a small proportion showing close-range interactions.

Although we did not investigate this quantitatively, our impression was that immediate responses to the introduction of the UAS into the ambient soundscape image were substantially reduced when birds were given time to habituate, which is supported by previous studies [3]. Thus, employing a strategic, flexible, and indirect flight pattern during the approach and ascent to the survey site allowed time for habituation and was crucial for minimizing disturbance, which is also previously demonstrated for waterbirds [40,43]. Furthermore, maintaining a minimum UAS deployment distance of 250 m from the survey site resulted in minimal visual disturbance.

4.2. Optimizing Bird Detection

During the recent decade, a growing number of studies have investigated UAS-based imaging as a game-changing survey tool, also increasingly in the Arctic [8,44] and Antarctic [9,45] regions, where remote and sheer cliffs often dominate the breeding environment for many seabird species. However, a rigorous approach to investigating the optical observing angling while surveying cliff nesting seabirds is, to our knowledge, to date lacking in the literature [1,3,36].

Our results provide a thorough evaluation of optimal camera pitch angles for maximizing detection and visibility of cliff-nesting fulmars in the Faroes. We found that the likelihood of missing visual contact with birds (“disappearance”) was strongly associated with viewing angle. Using binomial GAMMs, we identified a consistent optimal camera tilt range for full visibility, spanning from -30° to -1.3° , with peak detection (averaging 92%) at -13.8° , across diverse terrain types, slopes, erosion levels, and age groups. Importantly, it should be noted that most surveys typically comprise more than one flyby pass, which in turn will result in several tilt angles, and an almost perfect detection rate can therefore be expected compared to the single optimal tilt angle, which in our study yielded 92% visibility on average for all survey plots.

Interestingly, terrain type and bird age group significantly influenced the optimal viewing angle, with shallower and more eroded sites requiring greater downward tilt. In this context, the lower peak detection for grass vegetation, which required a broader detection interval to reach 100% detection rates compared to sites with bare rock and mixed vegetation types, should be considered when planning a survey. Moreover, a moderate positive correlation between survey elevation and the optimal pitch angle suggests that higher sites require less steep camera tilts, highlighting the need to dynamically adjust camera settings based on plot elevation and local geomorphology. The optimal pitch angle also varied among islands, reflecting geographic differences in cliff morphology.

Consequently, southern and central islands with more pronounced ledges required steeper angles compared to the more moderate slopes of the northern islands. As such, UAS survey protocols will benefit from camera tilt tailored to local terrain and environmental conditions in order to maximize detection rates and data quality for cliff-nesting seabirds. Finally, light intensity and solar angle may also affect detectability and the optimal pitch angle. Future analyses could examine this using camera timestamps as a proxy for cliff shadowing.

It is important to note that we have not performed independent ground truthing of the number of fulmars present in each study plot. We consider that this would not be logistically feasible and may further introduce new uncertainties due to the shift in counting method to manual counting in these physically difficult-to-access vertical places. The measures of visibility reported here are therefore relative to the maximum number of birds visible at any point of the survey. However, we believe that this number, in most cases, is a close approximation to the number of birds actually present.

4.3. Cliff Surveys Taken to New Heights

The use and integration of advanced UAS technology and camera systems were pivotal to the evaluation and success of our fulmar surveys at cliff sites. The live track and smart-capture functionalities enabled dynamic tracking and consistent focus on target individuals, ensuring data quality even as the UAS navigated complex cliff environments. Further, the use of the onboard LRF was critical for measuring continuous, accurate UAS-to-plot distances, which was a key factor for both safe operation and reliable behavioral interpretation.

These developments, as highlighted by a meta-study from 2025 [7] and supported by recent studies [6,15,46], represent a significant improvement of what was achievable with earlier technologies just a few years ago. The synergy of hardware and software facilitated not only high-precision documentation of fulmar responses but also the synchronization of behavioral observations with detailed flight metadata, such as altitude, camera angle, and trajectory. This hardware–software integration highlights the expanding potential for UAS platforms to deliver reliable, reproducible data in ornithological research, particularly for species in inaccessible or hazardous locations [3,5,47].

Our experiences highlight the critical importance of precise distance measurement, flexible camera control, and robust metadata collection to maximize the accuracy and reproducibility of aerial wildlife monitoring. These innovations enabled us to establish practical guidelines for minimizing disturbance and optimizing observation angles, advancing the potential for effective, non-invasive monitoring of cliff-nesting seabirds.

However, in our study, the individual detected and investigated birds were remotely detected with either the UAS or through binoculars, but were, for obvious practical reasons, not confirmed by ground truthing, e.g., manual or physical count of the birds in the survey plots. Additionally, the differentiation between incubating and resting adult fulmars based on bird posture posed a potential uncertainty. In some cases, such differentiation in the video sequences proved challenging and required training of the field observer.

In our study, the use of the relatively large industrial-grade DJI Matrice 300 RTK entailed a considerable visual and acoustic footprint, and the disturbance thresholds should therefore be regarded in this context. Smaller and quieter consumer-grade drones may elicit weaker responses and permit surveys at shorter distances, although this requires direct testing. At the same time, smaller UASs may in some cases cause greater disturbance due to higher-frequency noise and a smaller silhouette that could more closely resemble a natural aerial predator, in contrast to the larger platforms with a lower-frequency and more constant hum [48]. Comparative studies across UAS classes would help clarify how transferable disturbance thresholds are among platforms.

4.4. Practical Guidelines—A Promising Tool

Establishing practical guidelines to minimize disturbance remains paramount for ethical and reliable use of UAS in wildlife monitoring. Our systematic analysis, incorporating both UAS-based video and observer-based flyby records, emphasizes that fulmar responses are shaped by a multitude of factors, including breeding status (incubating versus resting), environmental conditions, and terrain morphology (Table 2). These insights are consistent with recent literature, which highlights the roles of flight initiation, flight patterns, and survey distance in mitigating disturbance [3,7,8]. Looking ahead, the development of robust protocols will require a balancing of the need to minimize disturbance and the ambition to optimize image quality, ensuring that UAS surveys not only avoid undue impacts on sensitive species but also deliver reliable data for research and conservation. Bird-to-UAS interactions should be assessed by evaluating across varying weather, lighting, and background conditions. Furthermore, possible differences in behavioral responses and the suitability of the surveying method could be evaluated according to the type of nesting environment. In addition, species-specific sensitivities should be considered when designing survey strategies.

Table 2. Practical guidelines and recommendations for reliable and repeatable UAS surveys of cliff-nesting fulmars. The following parameters are summarized: preflight and initial parameters, minimum flight distance, optimal camera tilt, survey site considerations, and study design.

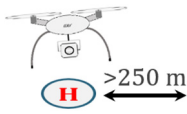
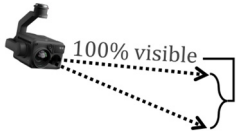
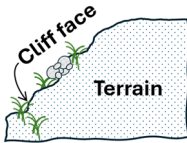
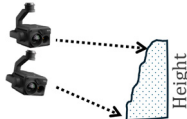
Guideline Category		Recommendation	Rationale
<i>Preflight and initial parameters</i>			
	Launch distance	Launch the UAS at least 250 m from the survey site when possible.	A greater initial distance appeared to reduce immediate disturbance and allowed birds time to habituate before the survey began.
	Approach strategy	Use a slow, indirect, and flexible approach path rather than a direct approach.	Strategic flight paths helped reduce disturbance and allowed habituation to the UAS presence.
<i>Minimum survey distance</i>			
Behavioral assessment minimizing responses		Maintain a UAS-to-bird distance of at least 57.5 m during surveys, especially in areas with mixed or non-incubating birds.	Vigilance responses began at 57.5 m in mixed groups and were therefore used as the conservative disturbance threshold.
	Bird activity: Incubating	Avoid flying closer than 32.9 m even when only incubating birds are present.	Incubating fulmars showed measurable vigilance from 32.9 m.
	Bird activity: Resting	Flying closer than 111 m can provoke responses from resting birds.	Plots with only resting fulmars showed earlier vigilance (111 m)

Table 2. Cont.

Guideline Category	Recommendation	Rationale	
Observation angles/camera tilt			
	General optimum	Aim for a camera tilt near -13.8° during surveys.	This angle gave the highest average detection, with about 92–93% visibility across all plots.
	Full coverage range	Cover a tilt range of approx. -30° to -1.3° across all survey plots.	Full visibility across habitat types required a broader tilt interval.
Survey site considerations			
	Terrain adjustments	Adjust tilt according to terrain: use less downward tilt on bare rock/steeper sites and more tilt in grassy, shallow, or eroded slopes.	Optimal pitch varied significantly with vegetation, slope, and erosion, affecting how quickly birds disappeared from view.
	Elevation adjustment	At higher-elevation plots, use a slightly less steep downward tilt.	Optimal pitch showed a positive relationship with elevation, indicating cliff height as a factor.
	Weather adjustments	Prefer surveys in lower wind and, where feasible, more overcast conditions.	Stronger winds increased response duration and repetition, while thicker cloud cover was associated with fewer responses.

5. Conclusions

This study demonstrated that UAS are a valuable tool for enhanced monitoring of cliff-nesting seabirds, in particular the North Atlantic fulmar population. We developed a customizable flight protocol and practical guidelines to minimize disturbance effects while simultaneously maximizing detection rates and data quality. We hope with this study to lay a key stone for the development of protocols for semi-automated surveying flight paths and further image annotation, including post hoc workflows for the detection and identification of cliff nesting seabirds.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/drones10070490/s1>, Table S1: Overview of the study sites; Figure S1: Overview of the performed UAS flights; Figure S2: Examples of behavioral responses; Table S2: Video post-processing note sheet for responses; Table S3: Baseline and benchmark for site characteristics; Figure S3: Examples of survey plots; Table S4: Video post-processing note sheet for observer angles; Figure S4: Observed distances of fulmar behavioral alteration to UAS proximity; Figure S5: Pooled behavioral response analysis of fulmars to UAS proximity; Figure S6: Relationships between environmental variables and fulmar response; Figure S7: Distribution of pitch angles for fulmar disappearance events in relation to direction; Figure S8: Noted pitch angles for fulmar disappearances; Table S5: Pairwise tests for differences in optimal pitch angle and terrain; Figure S9: Predicted optimal angles according to investigated island.

Author Contributions: Conceptualization, J.H.F.C., M.F. and S.H.; methodology, J.H.F.C., M.F. and S.H.; formal analysis, J.H.F.C., M.F. and M.B.G.; investigation, J.H.F.C.; data curation, J.H.F.C.; writing—original draft preparation, J.H.F.C.; writing—review and editing, J.H.F.C., M.F., M.B.G. and S.H.; visualization, J.H.F.C.; supervision, S.H. and M.F.; project administration, M.F. and S.H.; funding acquisition, J.H.F.C., M.F. and S.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Aage V. Jensen Charity Foundation (grant of 14 February 2022) for project funding and Brødrene Hartmanns Fond (grant of 12 April 2021, grant number A36734) for field equipment.

Data Availability Statement: The raw data, including images, video sequences, and annotating tables, that support the conclusions of this article will be made available on request from the lead author.

Acknowledgments: We would like to thank Jens-Kjeld Jensen for providing invaluable local insights and advice for the study setup, as well as Leivur Janus Hansen and Jón Aldará for their support with the study setup and field assistance. Further thanks to Sólfinn Kjærbo (Suðuroy) and Dánjal Petur Højgaard (Eysturoy) for guidance in the field and sharing specific knowledge on the local fulmar sites.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

UAS	Unoccupied Aircraft Systems
GSD	Ground sample distances
AMSL	Elevation above mean sea level
ASL	Above sea level
LRF	Laser range finder
SRT	SubRip Text file
SCAM	Shape-constrained additive models
GAMM	Generalized additive mixed model

References

- Walsh, P.M.; Halley, D.J.; Harris, M.P.; del Nevo, A.; Sim, L.M.W.; Tasker, M.L. *Seabird Monitoring Handbook for Britain and Ireland: A Compilation of Methods for Survey and Monitoring of Breeding Seabirds*; Walsh, P.M., Ed.; Joint Nature Conservation Committee: Peterborough, UK, 1995; ISBN 187370173x.
- Black, C.E. Spying on Seabirds: A Review of Time-Lapse Photography Capabilities and Limitations. *SEABIRD* **2018**, *31*, 1–14. [\[CrossRef\]](#)
- Edney, A.J.; Hart, T.; Jessopp, M.; Banks, A.; Clarke, L.; Cugniere, L.; Elliot, K.; Juarez Martinez, I.; Kilcoyne, A.; Murphy, M.; et al. Best Practices for Using Drones in Seabird Monitoring and Research. *Mar. Ornithol.* **2023**, *51*, 265–280. [\[CrossRef\]](#)
- Hayes, M.C.; Gray, P.C.; Harris, G.; Sedgwick, W.C.; Crawford, V.D.; Chazal, N.; Crofts, S.; Johnston, D.W. Drones and Deep Learning Produce Accurate and Efficient Monitoring of Large-Scale Seabird Colonies. *Ornithol. Appl.* **2021**, *123*, duab022. [\[CrossRef\]](#)
- Frederiksen, M.; Layton-Matthews, K.; Bennett, S.; Castenschiold, J.H.F.; Cruz-Flores, M.; Edney, A.J.; Fauchald, P.; Franklin, K.A.; Guímaro, H.R.; Hereward, H.F.R.; et al. Opportunities and Challenges for New Technologies in Seabird Population Monitoring. *ICES J. Mar. Sci.* **2025**, *82*, fsaf115. [\[CrossRef\]](#)
- Barnas, A.F.; Chabot, D.; Hodgson, A.J.; Johnston, D.W.; Bird, D.M.; Ellis-Felege, S.N. A Standardized Protocol for Reporting Methods When Using Drones for Wildlife Research. *J. Unmanned Veh. Syst.* **2020**, *8*, 89–98. [\[CrossRef\]](#)
- Anderson, K.; Gonzalez, F.; Gaston, K.J. Drones in Ecology: Ten Years Back and Forth. *Bioscience* **2025**, *75*, 664–680. [\[CrossRef\]](#) [\[PubMed\]](#)
- Bishop, A.M.; Brown, C.L.; Christie, K.S.; Kettle, A.B.; Larsen, G.D.; Renner, H.M.; Younkens, L. Surveying Cliff-Nesting Seabirds with Unoccupied Aircraft Systems in the Gulf of Alaska. *Polar Biol.* **2022**, *45*, 1703–1714. [\[CrossRef\]](#)
- Weimerskirch, H.; Prudor, A.; Schull, Q. Flights of Drones over Sub-Antarctic Seabirds Show Species- and Status-Specific Behavioural and Physiological Responses. *Polar Biol.* **2018**, *41*, 259–266. [\[CrossRef\]](#)

10. Chabot, D.; Bird, D.M. Evaluation of an Off-the-Shelf Unmanned Aircraft System for Surveying Flocks of Geese. *Waterbirds Int. J. Waterbird Biol.* **2018**, *35*, 170–174.
11. Jolly, D.W.; Passey, S.R.; Vosgerau, H.; Sørensen, E.V. Volcanic Landscape Controls on Pre-Rift to Syn-Rift Volcano Sedimentary Systems: The Prestfjall Formation Eruptive Hiatus, Faroe Islands Basalt Group, Northeast Atlantic. *Earth Environ. Sci. Trans. R. Soc. Edinb.* **2022**, *113*, 75–98. [\[CrossRef\]](#)
12. Nørrevang, A. *Fuglefangsten På Færøerne*, 1st ed.; Rhodos, Copenhagen: København, Denmark, 1977; ISBN 8774966189.
13. Jensen, J.-K.; Sørensen, S. *Birds of the Faroe Islands—Facts and Numbers*; Forlagid i Støplum: Tórshavn, Faroe Islands, 2015; ISBN 978-99918-77-06-8.
14. Edney, A.J.; Wood, M.J. Applications of Digital Imaging and Analysis in Seabird Monitoring and Research. *Ibis* **2020**, *163*, 317–337. [\[CrossRef\]](#)
15. Geldart, E.A.; Barnas, A.F.; Semeniuk, C.A.D.; Gilchrist, H.G.; Harris, C.M.; Love, O.P. A Colonial-Nesting Seabird Shows No Heart-Rate Response to Drone-Based Population Surveys. *Sci. Rep.* **2022**, *12*, 18804. [\[CrossRef\]](#) [\[PubMed\]](#)
16. Jensen, J.-K. *The Fulmar on the Faroe Islands*, 3rd ed.; Jens-Kjeld Jensen: Nolsoy, Faroe Islands, 2019; ISBN 978-99918-3-349-1.
17. Olsen, I.; Hammer, S.; Dinesen, L.; Sonne, J. Population Trends of Marine versus Terrestrial Bird Species on Skúgvoy, Faroe Islands, 1961–2023. *Bird Study* **2025**, *72*, 180–192. [\[CrossRef\]](#)
18. Parsons, M.; Mitchell, I.; Butler, A.; Ratcliffe, N.; Frederiksen, M.; Foster, S.; Reid, J.B. Seabirds as Indicators of the Marine Environment. *ICES J. Mar. Sci.* **2008**, *65*, 1520–1526. [\[CrossRef\]](#)
19. Frederiksen, M. Seabirds in the North East Atlantic. Summary of Status, Trends and Anthropogenic Impact. In Proceedings of the Workshop: Action Plan for Seabirds in Western-Nordic Areas, Malmö, Sweden, 4–5 May 2010; pp. 21–24.
20. Frederiksen, M.; Anker-Nilssen, T.; Schekkerman, H.; Dierschke, V.; Parsons, M.; Marra, S.; Mitchell, I. Model-based Assessment of Marine Bird Population Status Using Monitoring of Breeding Productivity and Abundance. *Ibis* **2025**, *166*, 940–950. [\[CrossRef\]](#)
21. Burg, T.M.; Bird, H.; Lait, L.; Brooke, M.d.L. Colonization Pathways of the Northeast Atlantic by Northern Fulmars: A Test of James Fisher’s ‘out of Iceland’ Hypothesis Using Museum Collections. *J. Avian Biol.* **2014**, *45*, 209–218. [\[CrossRef\]](#)
22. Hatch, S.A.; Nettleship, D.N. Northern Fulmar (*Fulmarus glacialis*). In *Birds of North America Online*; Poole, A., Ed.; Cornell Lab of Ornithology: Ithaca, NY, USA, 1998.
23. Statistics Iceland Hunting 1995–2020. Available online: https://px.hagstofa.is/pxen/pxweb/en/Atvinnuvegir/Atvinnuvegir_landbunadur_landveidi/LAN10303.px (accessed on 18 October 2025).
24. Danielsen, J. Diurnal Activity Patterns Suggest Nocturnal Foraging in Northern Fulmar (*Fulmarus glacialis*)/Dagligt Virksemi Hjá Havhesti (*Fulmarus glacialis*) Bendir á, at Hann Leitar Sær Føði Um Náttina. *Fróðskaparrit—Faroese Sci. J.* **2017**, *59*, 113–121. [\[CrossRef\]](#)
25. Jarrett, D.; Calladine, J.; Cotton, A.; Wilson, M.W.; Humphreys, E. Behavioural Responses of Non-Breeding Waterbirds to Drone Approach Are Associated with Flock Size and Habitat. *Bird Study* **2020**, *67*, 190–196. [\[CrossRef\]](#)
26. Mallory, M.L.; Forbes, M.R. Costly Pre-Laying Behaviours and Physiological Expenditures by Northern Fulmars in the High Arctic. *Écoscience (Sainte-Foy)* **2008**, *15*, 545–554. [\[CrossRef\]](#)
27. Landsverk Weather Cameras. Available online: <https://www.landsverk.fo/?id=837> (accessed on 18 October 2025).
28. R Development Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2025.
29. Pya, N.; Wood, S.N. *Shape Constrained Additive Models*; Kluwer Academic Publishers: Alphen aan den Rijn, The Netherlands, 2025; Volume 25.
30. Muggeo, V.M.R. Estimating Regression Models with Unknown Break-Points. *Stat. Med.* **2003**, *22*, 3055–3071. [\[CrossRef\]](#) [\[PubMed\]](#)
31. Muggeo, V.M.R. Segmented: An R Package to Fit Regression Models with Broken-Line Relationships. *R News* **2008**, *8*, 20–25.
32. Wickham, H. *Ggplot2: Elegant Graphics for Data Analysis*, 2nd ed.; Use R! Springer International Publishing: Cham, Switzerland, 2016; ISBN 9783319242750.
33. Spearman, C. The Proof and Measurement of Association between Two Things. *Am. J. Psychol.* **1904**, *15*, 72–101. [\[CrossRef\]](#) [\[PubMed\]](#)
34. Granadeiro, J.P.; Andrade, J.; Palmeirim, J.M. Modelling the Distribution of Shorebirds in Estuarine Areas Using Generalised Additive Models. *J. Sea Res.* **2004**, *52*, 227–240. [\[CrossRef\]](#)
35. Wood, S.N. *Generalized Additive Models: An Introduction with R*, 2nd ed.; CRC Press: Boca Raton, FL, USA, 2017; ISBN 9781498728348.
36. Tyndall, A.A.; Nichol, C.J.; Wade, T.; Pirrie, S.; Harris, M.P.; Wanless, S.; Burton, E. Quantifying the Impact of Avian Influenza on the Northern Gannet Colony of Bass Rock Using Ultra-High-Resolution Drone Imagery and Deep Learning. *Drones* **2024**, *8*, 40. [\[CrossRef\]](#)
37. Cipriano, G.; Santacesaria, F.C.; Fanizza, C.; Cherubini, C.; Crugliano, R.; Maglietta, R.; Ricci, P.; Carlucci, R. Social Structure and Temporal Distribution of Tursiops Truncatus in the Gulf of Taranto (Central Mediterranean Sea). *J. Mar. Sci. Eng.* **2022**, *10*, 1942. [\[CrossRef\]](#)

38. Rush, G.P.; Clarke, L.E.; Stone, M.; Wood, M.J. Can Drones Count Gulls? Minimal Disturbance and Semiautomated Image Processing with an Unmanned Aerial Vehicle for Colony-Nesting Seabirds. *Ecol. Evol.* **2018**, *8*, 12322–12334. [[CrossRef](#)] [[PubMed](#)]
39. Brisson-Curadeau, É.; Bird, D.; Burke, C.; Fifield, D.A.; Pace, P.; Sherley, R.B.; Elliott, K.H. Seabird Species Vary in Behavioural Response to Drone Census. *Sci. Rep.* **2017**, *7*, 17884. [[CrossRef](#)] [[PubMed](#)]
40. Holm, T.E.; Rasmussen, L.M.; Castenschiold, J.H.F.; Koffijberg, K.; Bregnballe, T. *Usage of Drones in Assessing Bird Numbers Along the East Atlantic Flyway*; DCE—Danish Centre for Environment and Energy: Roskilde, Denmark, 2024.
41. Pandat, A.; Rajasekhar, P.; Vinod, G.; Shukla, R. Strategies for Improved Out-of-Distribution Detection in Drone vs. Bird Classification. *Procedia Comput. Sci.* **2025**, *259*, 398–407. [[CrossRef](#)]
42. Valle, R.G.; Scarton, F. Do Oystercatchers Hate Drones? A Comparison of Flight Initiation Distances of Four Wader Species in Response to Drone Intrusion. *Wader Study* **2025**, *131*, 214–218. [[CrossRef](#)]
43. Castenschiold, J.H.F.; Bruhn, D.; Pertoldi, C.; Bregnballe, T. Monitoring Roosting Waterbirds: The Use of Drones to Overcome the Challenge of Hidden Individuals in Blind Zones on Intertidal Flats. *Wader Study* **2023**, *130*, 239–253. [[CrossRef](#)]
44. Hong, S.J.; Han, Y.; Kim, S.Y.; Lee, A.Y.; Kim, G. Application of Deep-Learning Methods to Bird Detection Using Unmanned Aerial Vehicle Imagery. *Sensors* **2019**, *19*, 1651. [[CrossRef](#)] [[PubMed](#)]
45. Korczak-Abshire, M.; Zmarz, A.; Rodzewicz, M.; Kycko, M.; Karsznia, I.; Chwedorzewska, K.J. Study of Fauna Population Changes on Penguin Island and Turret Point Oasis (King George Island, Antarctica) Using an Unmanned Aerial Vehicle. *Polar Biol.* **2019**, *42*, 217–224. [[CrossRef](#)]
46. Brisson-Curadeau, É.; Lacombe, R.; Gousy-Leblanc, M.; Poirier, V.; Jackson, L.; Petalas, C.; Miranda, E.; Eby, A.; Baak, J.; Léandri-Breton, D.; et al. A Meta-analysis of the Impact of Drones on Birds. *Front. Ecol. Environ.* **2025**, *23*, e2809. [[CrossRef](#)]
47. Pfeifer, C.; Knetsch, S.; Maercker, J.; Mustafa, O.; Rümmler, M.-C.; Brenning, A. Exploring the Potential of Aerial Drone Imagery to Distinguish Breeding Adélie (*Pygoscelis adeliae*), Chinstrap (*Pygoscelis antarcticus*) and Gentoo (*Pygoscelis papua*) Penguins in Antarctica. *Ecol. Indic.* **2025**, *170*, 113011. [[CrossRef](#)]
48. Afridi, S.; Laporte-Devlyder, L.; Maalouf, G.; Kline, J.M.; Penny, S.G.; Hlebowicz, K.; Cawthorne, D.; Lundquist, U.P.S. Impact of Drone Disturbances on Wildlife: A Review. *Drones* **2025**, *9*, 311. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.