RESEARCH ARTICLE

Automated counting of nesting Adélie penguins at Cape Hallett, Ross Sea, Antarctica, using very high-resolution drone images and the YOLOv11 object detection model

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Abstract

Adélie penguins (*Pygoscelis adeliae*) are vital bioindicators of environmental change in Antarctica. This study evaluated the state-of-the-art You Only Look Once version 11 (YOLOv11) deep learning-based object detection model and very high-resolution (VHR) drone images to comprehensively census nesting Adélie penguins on Cape Hallett, Ross Sea, Antarctica. A total of 554 drone images, acquired from four independent flights in November 2017, were mosaicked at a spatial resolution of approximately 7.1 mm and then segmented into small-size image tiles for nesting penguin detection. An overlap was applied between adjacent small image tiles to prevent the loss of detected nesting penguins caused by segmentation cuts. The detection results from the overlapping areas in adjacent image tiles were consolidated using a predefined distance threshold of 0.1 m to eliminate duplicate detections. The deep learning-based object detection model achieved a detection precision of 95.3%, a recall of 97.6% at a confidence level of 0.5 and an estimated population of 47 340 nesting penguins. The derived population estimate closely agreed with results from an aerial survey conducted in the same year. Some nesting penguins were missed in dark land areas where colour contrast was low, and nesting-penguin-like rocks, shadows and wet areas caused false detections. Nevertheless, the approach demonstrated high accuracy, efficiency and scalability. This study highlights the potential of combining VHR drone images and deep learning-based object detection for low-disturbance penguin monitoring, providing data to support conservation strategies and to assess the impacts of climate change and human activities on Antarctic ecosystems.

Keywords

Drone imagery; You Only Look Once; deep learning; low-disturbance monitoring

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Abbreviations

CCAMLR: Commission for the Conservation of Antarctic Marine Living Resources
IoU: intersection over union
mAP: mean average precision
MPA: Marine Protected Area
MS COCO: Microsoft Common Objects in Context
R-CNN: Regions with Convolutional Neural Networks
RGB: red, green, blue
SCAR: Scientific Committee on Antarctic Research
VHR: very high-resolution
YOLO: You Only Look Once

Introduction

Adélie penguins (*Pygoscelis adeliae*) are recognized as crucial bioindicators of environmental changes in Antarctica, particularly in response to fluctuating sea-ice conditions (Emmerson & Southwell 2008). As ice-dependent predators, these penguins provide valuable insights into subtle and substantial shifts across Antarctic ecosystems (Cimino et al. 2016). Sea ice plays a central role in reproductive performance, with nearshore sea ice exerting a strong influence on breeding success (Emmerson & Southwell 2008). Changes in the extent and concentration of sea ice directly affect Adélie penguins' access to breeding sites and food-rich waters, ultimately shaping their population dynamics (Hu et al. 2013). Other environmental factors, including snow cover, air temperature and krill abundance, also influence Adélie penguin survival and reproductive success (Emmerson & Southwell 2008; Riaz et al. 2023). These interconnections underscore the necessity for the systematic monitoring of Adélie penguin colonies to better understand and mitigate the impacts of environmental change (Hu et al. 2013).

The Ross Sea, which hosts approximately 38% of the Antarctic Adélie penguin population, is a critical region

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for studying these penguins (Ainley 2002; Lyver et al. 2014). Long-term monitoring has revealed notable fluctuations in Adélie penguin populations in the Ross Sea, including a decline during the 1980s and 1990s, followed by recovery with an annual growth rate of 6% since 2001 (Lyver et al. 2014). This population rebound is attributed to improved sea-ice conditions, changes in prey availability and reduced human pressures such as commercial fishing (Ainley et al. 2010). Census efforts in the Ross Sea enhance the understanding of penguin population dynamics and contribute to evaluating the effectiveness of the Ross Sea Region MPA, which plays a vital role in ecosystem-based management in the Southern Ocean (Brooks et al. 2016).

Cape Hallett, a prominent Adélie penguin breeding site in the western Ross Sea, is a key case study area for understanding the impacts of environmental and human-induced changes. The site has experienced considerable disturbances, including the establishment and subsequent abandonment of a research station that caused notable declines in penguin populations during its operation. Long-term monitoring revealed the subsequent recolonization of Cape Hallett, offering valuable insights into the resilience and adaptability of Adélie penguins in response to anthropogenic activities and natural environmental fluctuations (Kim, Kim et al. 2023). Census efforts at Cape Hallett, spanning several decades, have provided a robust baseline for detecting population trends and understanding the broader ecological processes affecting penguin colonies (Young 1970; Antarctica New Zealand 2024).

Technological advancements have revolutionized Adélie penguin monitoring, enabling more efficient and accurate data collection across vast and remote areas (Strang et al. 2025). In particular, drone-based aerial surveys offer substantial advantages over traditional methods such as ground-based direct counts with handheld tally counters (Borowicz et al. 2018; Shah et al. 2020), as well as manual and semi-automated detection and counting from aerial photographs (McNeill et al. 2011; Lyver et al. 2014). When operated following appropriate flight protocols, drones can reduce direct human presence and associated disturbance to penguin colonies compared to ground-based surveys (Strang et al. 2025). However, previous studies have shown that penguin behavioural responses may still be observed even at flight altitudes of up to 50 m (Rümmler et al. 2016), underscoring the importance of careful drone operation. Under such controlled conditions, drones also facilitate the creation of VHR photomosaics, which can be analysed using advanced machine-learning algorithms to automate penguin counting (Bird et al. 2020). This reduction in human disturbance also enables more frequent and comprehensive monitoring without negatively affecting bird behaviour or breeding success (Fudala & Bialik 2022). The increased precision and efficiency contribute to the conservation of penguin populations and serve as an early warning system for the broader ecological effects of climate change in Antarctica (Hodgson et al. 2016).

Deep learning-based object detection techniques (Tuia et al. 2022) have advanced penguin monitoring using drone images. YOLO, a popular object detection algorithm, simultaneously performs localization and classification, offering a fast and accurate approach to analysing wildlife data. The evolution of YOLO algorithms has been well described (Gallagher & Oughton 2025; Jegham et al. 2025). Variations in Yolo for penguin detection (YoloPd) have resulted in improvements in the detection of Adélie penguin targets against complex backgrounds using images from helicopter-equipped camera (Wu et al. 2023). YoloPd outperformed classical detectors such as Faster R-CNNs by 8.5% in the mAP and surpassed the YOLOv7 detector by 2.3% in the F1-score (see definition below) with fewer parameters. Belyaev et al. (2024) successfully applied YOLOv8x, which offers the highest accuracy in the YOLOv8 family, to accurately count adults and chicks in a chinstrap penguin (*Pygoscelis antarcticus*) colony at Vapour Col, Deception Island, Antarctica, using VHR drone images.

YOLOv11, one of the latest versions of the YOLO series, was released in September 2024 and demonstrated superior real-time object detection performance with significant architectural enhancements (Sapkota & Karkee 2024). It enables superior feature extraction and spatial attention, achieving a mAP 50–95 value of 54.5% with an inference latency of approximately 13 milliseconds for YOLOv11x, the largest model variant, on the MS COCO data sets. Additionally, the YOLOv11m variant requires 22% fewer parameters than YOLOv8m, while maintaining comparable accuracy, making it highly efficient for tasks such as object detection, segmentation, pose estimation and oriented bounding box detection across diverse deployment environments (Khanam & Hussain 2024). Given these advancements, our objective was to evaluate the applicability and accuracy of this latest object detection model for monitoring Adélie penguin breeding populations.

This study aimed to evaluate the performance of the state-of-the-art YOLOv11 deep learning object detection model by combining it with VHR drone images to accurately detect and efficiently count nesting Adélie penguins on Cape Hallett. Separate data sets were used for training, validating and testing the detection model. Accuracy scores were compared to previous detection algorithms, including YOLOPd. We also evaluated the overall accuracy of the derived population estimate using the YOLOv11 detection model by comparing it to results of a traditional aerial survey from the same year. Through this process, we developed a protocol applicable to large-scale nesting Adélie penguin population surveys across the Ross Sea region, contributing not only to simple population counts but also to assessing ecological health and population trends.

Material and methods

Study area

Cape Hallett, at the northern tip of the Hallett Peninsula in Antarctica (Fig. 1a), hosts a large Adélie penguin colony. This colony is at Seabee Hook (72.319°S, 170.215°E) on the west side of the cape (Fig. 1b), between Edisto Inlet and Moubray Bay (Antarctic Treaty Secretariat 2021). This site is recognized as an Important Bird Area because of its substantial Adélie penguin population (Harris et al. 2015). The Cape Hallett area is also designated as Antarctic Specially Protected Area No. 106, covering approximately 53 ha (Antarctic Treaty Secretariat 2021). This designation aims to protect the unique biological diversity and habitats of the site, including the Adélie penguin colony.

The Cape Hallett penguin colony has a unique history of human interaction, making it an ideal site for studying the impact of human activity on Antarctic ecosystems. From 1956 to 1973, the area was home to the joint US–New Zealand Hallett Station, which was built directly within the penguin colony (Kim, Kim et al. 2023). This human presence substantially affected the breeding of the Adélie penguin population. Breeding populations declined from approximately 62 900 pairs in 1959 to 37 000 pairs in 1968, followed by a possible increase to 50 000 breeding pairs by 1972 and over 66 000 pairs in 1987 (Wilson et al. 1990). Subsequent surveys have indicated annual fluctuations, with the most recent breeding population estimate of 43 700 pairs in 2019 (Kim, Kim et al. 2023). Since the decommissioning and clean-up of the Hallett Station, this site has provided a unique opportunity to study ecosystem recovery following considerable disturbances. Breeding birds have begun to reoccupy former station sites, and the recovery process is the subject for ongoing scientific research (Antarctic Treaty Secretariat 2021). This history of human impacts, coupled with the availability of reliable historical data on Adélie penguin population changes, makes Cape Hallett an invaluable location for studying the long-term effects of human activity on Antarctic wildlife and their subsequent recovery.

Drone image acquisition and mosaicking

In this study, the incubation period was selected as the study period among the phases of the Adélie penguin breeding cycle, including incubation, guard and crèche (McLatchie et al. 2024). As a proxy for the number of breeding pairs, we estimated the number of nesting Adélie penguins during the incubation period. During this time, at least one adult from each breeding pair is always onshore (Strang et al. 2025). In another Adélie penguin colony in the Ross Sea, breeding penguins typically arrive at Ross Island between late October and early November. They construct pebble nests and usually lay

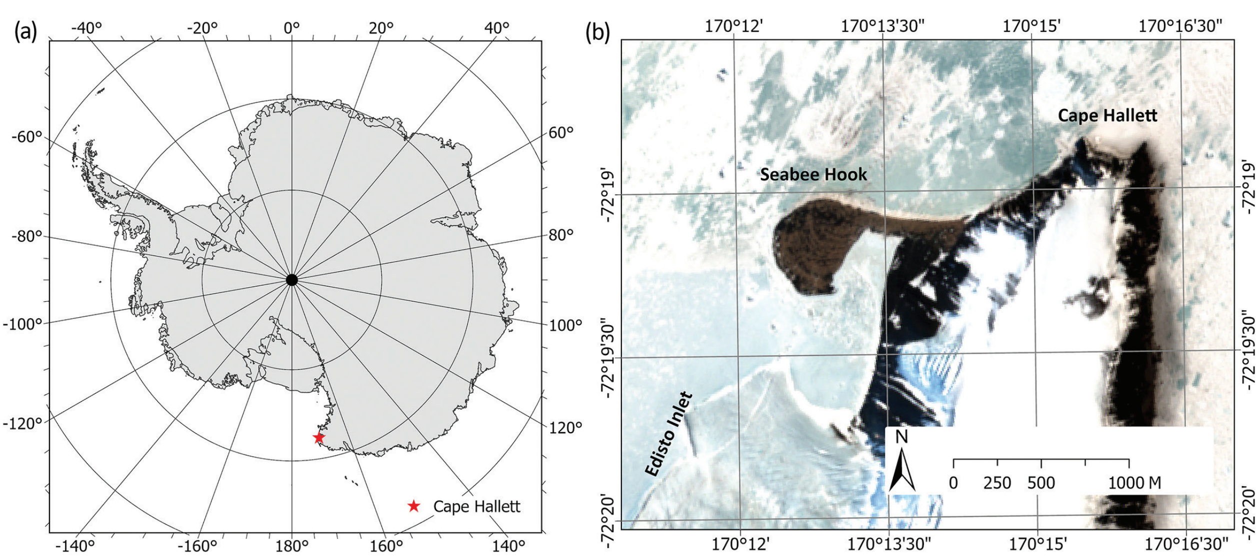

Fig. 1 (a) Location of Cape Hallett, Ross Sea, Antarctica, and (b) overview provided by Sentinel-2 satellite imagery acquired on 23 November 2018. The Antarctic coastline is sourced from Gerrish et al. (2024).

Table 1 Specifications of drone image acquisition.

Flight date	Flight duration	Number of images	Imaging specifications
25–26 Nov. 2017	Approximately 36 min across three independent flights due to battery replacements	550	Canon EOS 5DS camera with a 50 mm lens mounted on a DJI M600 drone
26 Nov. 2017	Selected four images from a flight lasting about 5 min	4	Canon EOS 5DS camera with a 24 mm lens mounted on a DJI M600 drone

one or two eggs by mid-November. The eggs hatch after approximately 35 days of incubation, and the chicks are cared for by both parents until they fledge in early February (Lyver et al. 2014).

A total of 554 drone images acquired during the incubation period over the Adélie penguin colonies on Cape Hallett, on 25–26 November 2017, were used (Table 1). The four images acquired using a 24 mm lens were used to supplement areas not captured with the 50 mm lens. The average imaging altitude for all flights was approximately 85.6 m above ground level. The acquired drone images were mosaicked using the structure-from-motion technique implemented in Agisoft Metashape software (Agisoft LLC, St. Petersburg, Russia). The processing workflow consisted of four steps: image alignment, extraction of a dense cloud from overlapping regions between images, generation of a digital elevation model from the dense cloud, and mosaicking of orthorectified images with colour correction (e.g., Hyun et al. 2019; Kim, Hyun et al. 2023).

Deep learning-based nesting penguin detection and counting

Counting nesting penguins ensures a precise estimate of breeding pairs and establishes baseline data for monitoring population trends. In this study, a deep learning-based object detection approach was used to count the nesting Adélie penguins following the workflow illustrated in Fig. 2. Image labelling was performed using Roboflow, a platform designed to streamline data set preparation for computer vision tasks (Hidayah et al. 2022). Roboflow offers tools for annotating images, managing datasets and augmenting data (Guarnido-Lopez et al. 2024), simplifying the process of labelling individual penguins, and preparing the data set for training, testing and validation of the deep learning object detection model. The detailed step-by-step methodology is presented below.

Large-size image tiling. The mosaicked image was divided into large image tiles to improve the analysis efficiency and avoid counting unnecessary areas. An overlap was specified between adjacent large tiles to ensure that the detected penguins were not lost owing to segmentation cuts. The size of the large image tiles was determined to be a whole-number multiple of the small-size image tiles, based on their dimensions and overlapping requirements.

Small-size image tiling. Similar to the large-size image tiling, an overlap was specified between adjacent small image tiles to prevent the loss of detected penguins caused by segmentation cuts. Each small-size image tile was used as training, testing and validation data for developing the deep learning object detection model, as well as input for counting nesting Adélie penguins across the entire mosaicked drone image using the trained model.

Image labelling. For selected small-size image tiles, detection reference areas corresponding to individual nesting penguins were established for training, testing, validation and performance testing of the nesting penguin detection model using the Roboflow annotation tool.

Defining the training, testing and validation data sets. A data set was prepared using nesting Adélie penguin labels and divided into training, validation and testing sets at a ratio of 7:2:1 for the detector.

Training the nesting penguin detector. The nesting Adélie penguin detector was developed by training it on designated training and validation data sets and evaluating its performance using a test data set.

Executing the nesting penguin detection. The trained nesting Adélie penguin detector was applied to preprocessed small-size image tiles. The centre points of the bounding boxes for individual nesting penguins were converted into point coordinates within the predefined coordinate reference system.

Integrating detected nesting penguins. The detection results of nesting Adélie penguins, in the form of point data, from the overlapping areas in adjacent small-size image tiles were consolidated using a specified distance threshold to merge duplicate detections.

Nesting penguin counting. The consolidated detection results were used to estimate the total number of nesting Adélie penguins across the entire study area.

Evaluating the detection model

Precision, defined as the proportion of true positive (TP) predictions to the total predicted positive cases (TP + false positive [FP]), quantifies the accuracy of the model's

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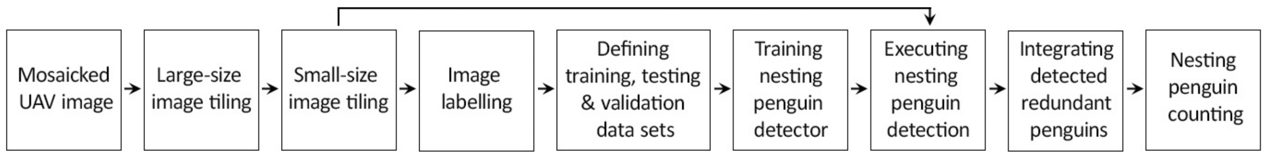

Fig. 2 Workflow for deep learning-based detection and counting of nesting Adélie penguins.

positive predictions. Recall, the ratio of TP predictions to the total actual positive cases (TP + false negative [FN]), reflects the model's effectiveness in identifying all relevant instances (Pacal et al. 2022). To provide a balanced assessment of model performance, the F1-score, the harmonic mean of precision and recall, was computed. This metric is useful when there is an imbalance between precision and recall (Casas et al. 2023). For the colony-wide census estimation, the confidence threshold was optimized on the validation data set using a step size of 0.05 by maximizing the F1-score.

The mAP is a widely used metric in object detection that evaluates the overall accuracy of a model by calculating the area under the precision-recall curve. This metric summarizes the trade-off between precision and recall across different confidence thresholds (Roy et al. 2023). The mAP at an IoU threshold of 0.5 (mAP 50) assesses model performance when a prediction is considered correct if the overlap between the predicted and ground-truth bounding boxes is at least 50%. To provide a more rigorous assessment of robustness, the mAP across a range of IoU thresholds from 0.50 to 0.95 (mAP 50–95) averages performance over increasingly strict overlap thresholds, providing a more rigorous evaluation of the model's robustness.

In addition, the nesting penguin count was compared with an aerial survey conducted in the same year as part of a long-term monitoring framework (Oceanites Inc. 2023) to provide an external reference for assessing the plausibility of the estimates based on VHR drone imagery and YOLOv11. The survey followed CCAMLR's Standard Method A3B (CCAMLR 2014), using high-altitude aerial photography and expert manual counts of occupied nests.

Results and discussion

Drone image mosaicking and preprocessing for training the YOLOv11 nesting Adélie penguin detection model

The mosaicked drone image (Fig. 3) measured 172 030 × 99 327 pixels with a spatial resolution of approximately 7.1 mm. As shown in Table 1, four images were captured using a wide-angle lens (24 mm). These images resulted in a lower spatial resolution of approximately 1.4 cm for the small portions mosaicked area. This area, defined by the four images, is indicated by the red boundary polygon in Fig. 3b.

The mosaicked drone image was divided into 180 large-size image tiles, each measuring 10 100 × 10 100 pixels, with an overlap of 100 pixels between adjacent tiles (Fig. 4a). This large-size image tiling process ensured that the study area focused on meaningfully photographed regions, eliminating large vacant tiles or those without colony areas. Subsequently, 73 selected large-sized image tiles were further divided into small image tiles, each measuring 600 × 600 pixels, with an overlap of 100 pixels between adjacent tiles to prevent the loss of detected penguins due to segmentation cuts (Fig. 4b). Each selected large-size image tile was subdivided into 400 small-size image tiles. Among these small image tiles, those containing nesting penguins were used to train the YOLOv11 object detection model and to detect and count nesting Adélie penguins using the trained model.

Training YOLOv11 nesting Adélie penguin detection model and accuracy assessment

Among the YOLOv11 variants, the YOLOv11x model was selected for training the nesting Adélie penguin detection model because it has been reported to achieve the highest mAP of all variants (Sapkota & Karkee 2024). A total of 216 small image tiles containing nesting Adélie penguins from two selected large-sized image tiles (Fig. 4a) were split and used to train (151 images), validate (43 images) and test (22 images) the YOLOv11 nesting Adélie penguin detection model. Vertical and horizontal flip augmentations were performed using the Roboflow platform to expand the labelled data sets. The training, validation and test data sets included 2851, 350 and 167 labels, respectively.

An example of the image-labelling process used to define the training, validation and testing of data sets for nesting Adélie penguin detection is shown in Fig. 5. Only clearly identified individuals in nests, as well as those lying or standing on nests (Fig. 5a), were labelled, whereas those moving or positioned outside the nests (Fig. 5b) were excluded during the labelling process. The nests were identified as structures composed of pebbles arranged in circular shapes (Lyver et al. 2014).

Using the labelled data sets, an initial configuration of 300 epochs was set on a single A100 graphic processing

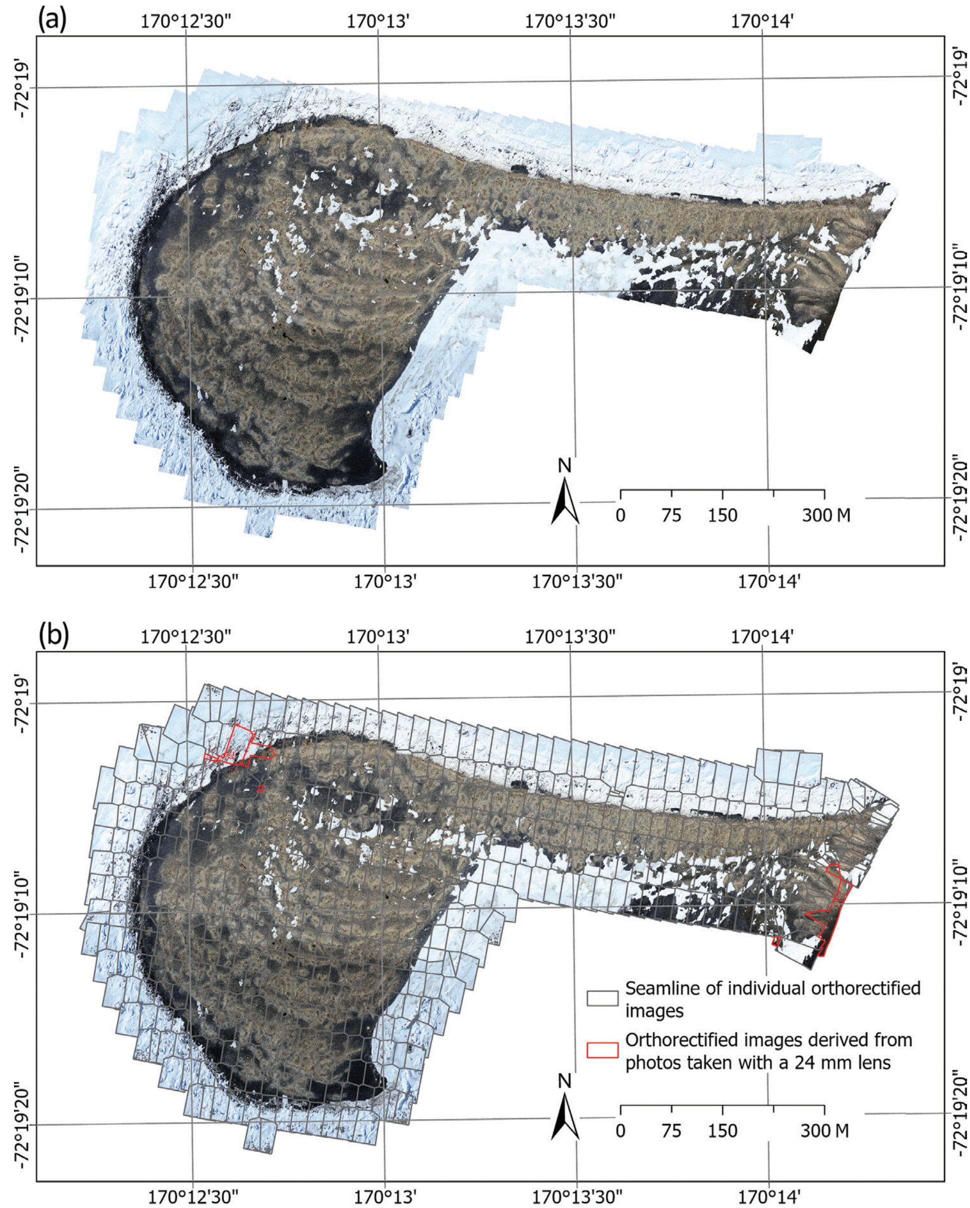

Fig. 3 (a) The entire mosaicked drone image of Cape Hallett. (b) Seamlines overlaid on the mosaicked drone image, with the red boundary polygon indicating areas derived from orthophotos captured using a 24 mm lens.

unit in the Google Colab runtime with a batch size of 32 to train the YOLOv11 nesting Adélie penguin detection model. The Adaptive Moment Estimation with Weight Decay optimizer was used with a learning rate of 0.002, momentum of 0.9, weight decay of 0.0005 and patience of 50 for early stopping.

The training process for the penguin detection model was terminated after 175 epochs, achieving a precision of 95.3% and a recall of 97.6% on the testing data set, evaluated at a confidence threshold of 0.5. The resulting F1-score was approximately 96.4%, confirming the model's high effectiveness in accurately detecting penguins while minimizing missed detections. These results underscore the model's capability to detect nearly all penguins with minimal errors. A mAP 50 value of 97.6% indicates that the model performed exceptionally well under the lenient criterion. The achievement of a mAP 50–95 of 74.1% underscores the model's strong performance, even under challenging evaluation conditions.

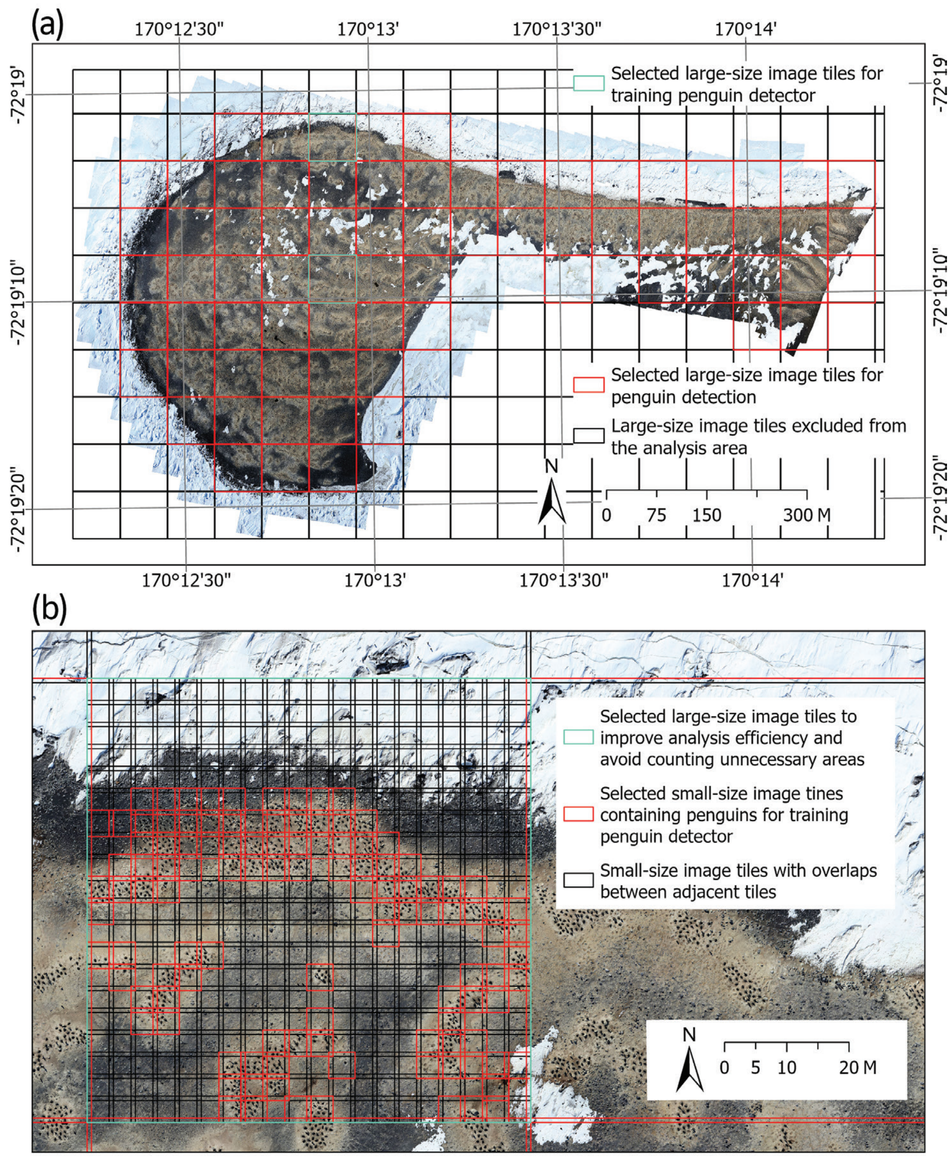

Fig. 4 Example of input image preprocessing for the nesting Adélie penguin detection model: (a) segmentation and selection of large-size image tiles; and (b) identification of small-size image tiles containing nesting penguins within the large tiles.

When quantitatively comparing these accuracy assessment results with previous studies that detected penguins using deep learning-based object detection methods and high-resolution colour imagery (Table 2), it was confirmed that the accuracy was higher in both F1-score and mAP 50 compared to studies that used Faster R-CNN, YOLOv7 and YOLOPd (Wu et al. 2023) and those that used RetinaNet (Hayes et al. 2021). In this comparison, we consider that, in addition to the object detection method, data set characteristics—such as spatial resolution—may have influenced the accuracy.

Because model training and evaluation were conducted using data from a single colony and a single acquisition period, the reported performance is inherently limited to site- and season-specific conditions. Additional validation across multiple colonies, background conditions and breeding seasons will be required to assess robustness and generalizability and to reduce the risk of overfitting to local visual characteristics.

Recent studies have demonstrated the increasing applicability of deep learning, including YOLO-based detectors, for Antarctic wildlife monitoring using UAV imagery, particularly for small-object detection in large-area surveys (Hinke et al. 2022; Wu et al. 2023; Belyaev et al. 2024; Cusick et al. 2024). In parallel, customized network architectures have been proposed for penguin detection to

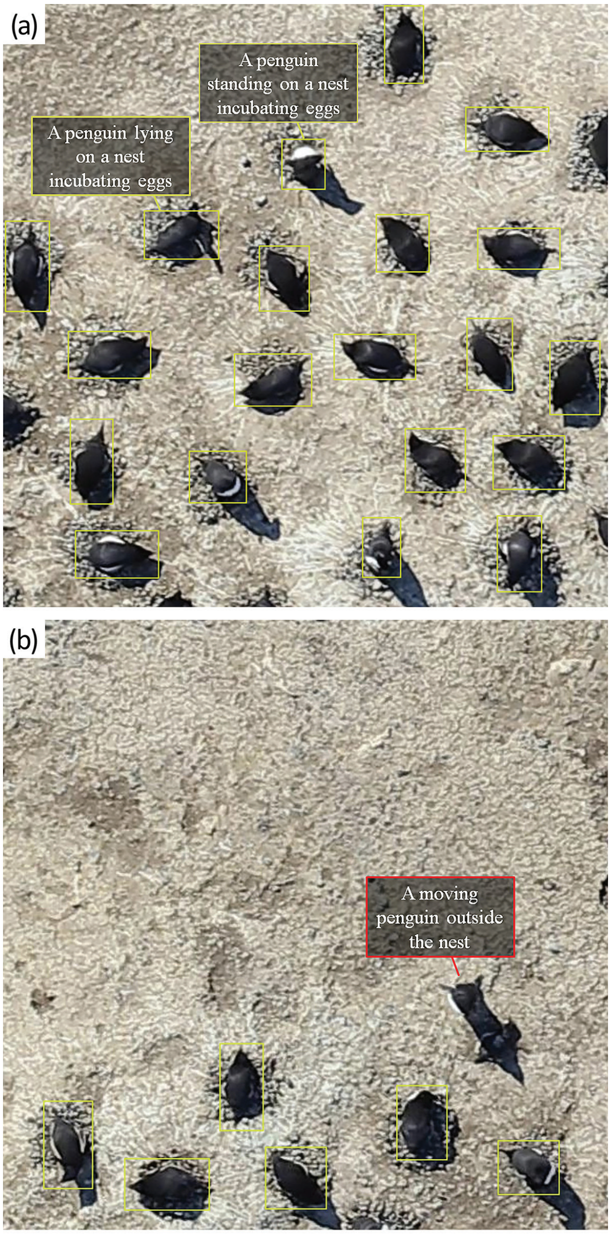

Fig. 5 Examples of the labelling process for individual nesting Adélie penguins: (a) labelled individual penguins located on nests; and (b) an excluded penguin moving or positioned outside a nest during labelling.

address challenges associated with dense object distributions, heterogeneous backgrounds and variable illumination conditions (Wu et al. 2023). Semantic segmentation and transformer-based approaches have also been explored to improve fine-scale object delineation and contextual understanding (Gibril et al. 2024; Li et al. 2024); however, their higher annotation requirements and computational complexity may limit their practicality for colony-wide census applications. In this context, the present study adopts a state-of-the-art YOLOv11-based detection framework and demonstrates reliable colony-wide penguin population assessment by achieving consistently high precision and recall from VHR UAV imagery.

Counting nesting Adélie penguins on Cape Hallett

The optimal confidence threshold for colony-wide detection of nesting Adélie penguins was determined using the trained model. Using the validation data set, the confidence threshold was systematically varied from 0.1 to 0.9 in increments of 0.05, and the F1-score was evaluated at each step. The confidence threshold of 0.65, which maximized the F1-score (0.974), was selected for detecting nesting Adélie penguins across the entire study area.

A total of 29 200 small-size image tiles, derived from the selected 73 large-size image tiles, were processed using the trained YOLOv11 object detection model to count nesting Adélie penguins across the entire Cape Hallett area. For ease of use, the detection results were converted into point coordinates in the Universal Transverse Mercator Zone 59S based on the metric system by extracting the centre points of the bounding boxes for individual penguins. These points were merged and overlaid onto the mosaicked drone images. Duplicate detections were consolidated using a specified distance threshold of 0.1 m (Fig. 6) to address positional discrepancies in the detected centre points within overlapping areas of adjacent small-size image tiles.

After eliminating duplicate detections, the total number of nesting Adélie penguins across the entire Cape Hallett area was estimated to be 47 340, with a confidence level of 0.65 (Fig. 7a). Visual inspection revealed the presence of undetected penguins (Fig. 7b) and incorrectly identified detections (Fig. 7c). Undetected penguins were predominantly found in dark land areas, which are uncommon nesting sites typically characterized by reddish guano and offering less colour contrast between the land and the penguins. Additionally, penguins in these areas remained undetected when exhibiting non-typical nesting postures, such as standing on their nests. Conversely, false detections are generally caused by rocks, shadows, wet areas or a combination of these elements, which mimic the appearance of nesting Adélie penguins.

The nesting Adélie penguin count was compared with an independent aerial survey-based count of 48 572 nests conducted in December 2017 (Oceanites Inc. 2023). The aerial survey was not originally designed for methodological comparison with drone-based analyses, but represents an independent census conducted within a

Table 2 Comparison with previous studies of deep learning-based penguin detection.

Method	Data	F1-score (%)	mAP 50 (%)	References
Faster R-CNN	Images from a digital camera mounted on a helicopter with a spatial resolution of 5 cm	81.8, 83.1 (depending on the selected backbone, confidence threshold of 0.5)	78.4, 79.7 (depending on the selected backbone)	Wu et al. 2023
YOLOv7	As above	85.7, 85.9 (depending on the selected backbone, confidence threshold of 0.5)	87.3, 87.5 (depending on the selected backbone)	Wu et al. 2023
YOLOPd	As above	88.0	89.4	Wu et al. 2023
RetinaNet	Drone images with spatial resolutions varying from 4.8 mm to 5 cm	84.5 (confidence threshold of 0.5)	87.2	Hayes et al. 2021
YOLOv11x	Drone images with a spatial resolution of 7.1 mm	96.4 (confidence threshold of 0.5)	97.6	this study

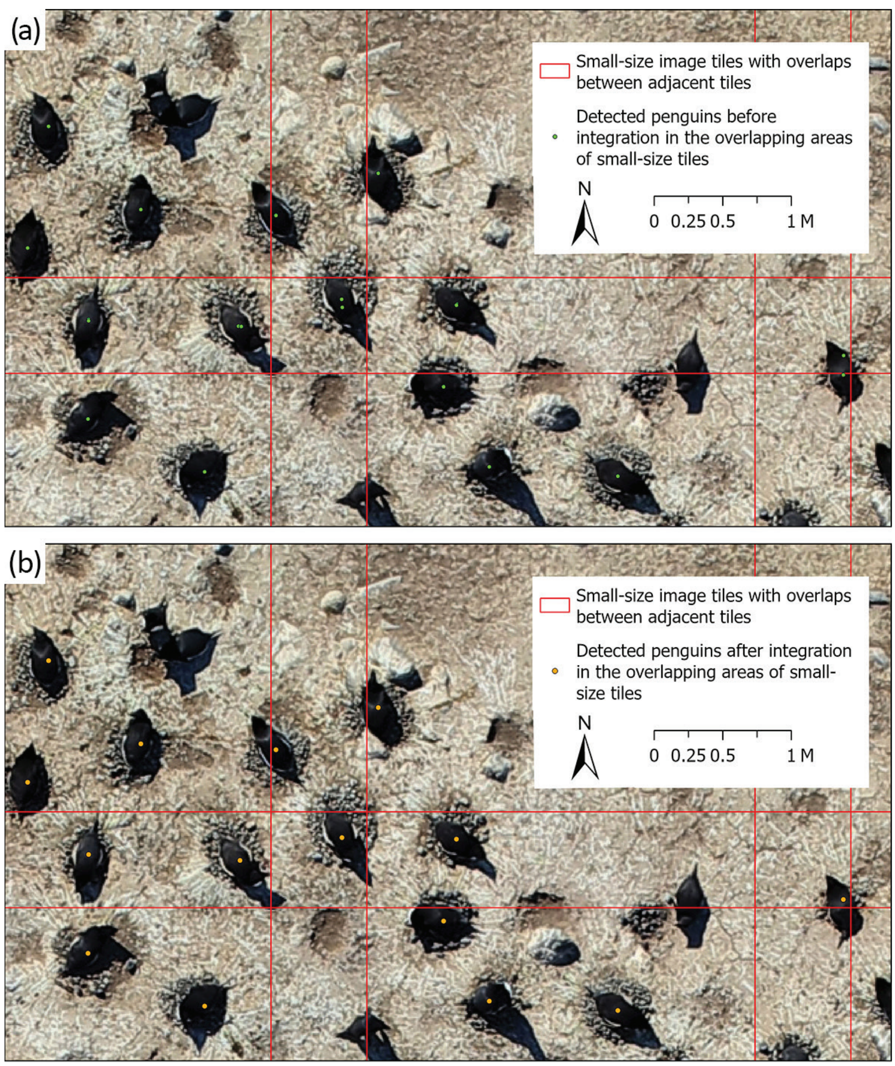

Fig. 6 Centre points of the bounding boxes for detected individual nesting Adélie penguins overlaid on the mosaicked drone image: (a) initial points showing positional discrepancies in overlapping areas between adjacent small-size image tiles; and (b) points after duplicate detections were consolidated using a specified distance threshold of 0.1 m.

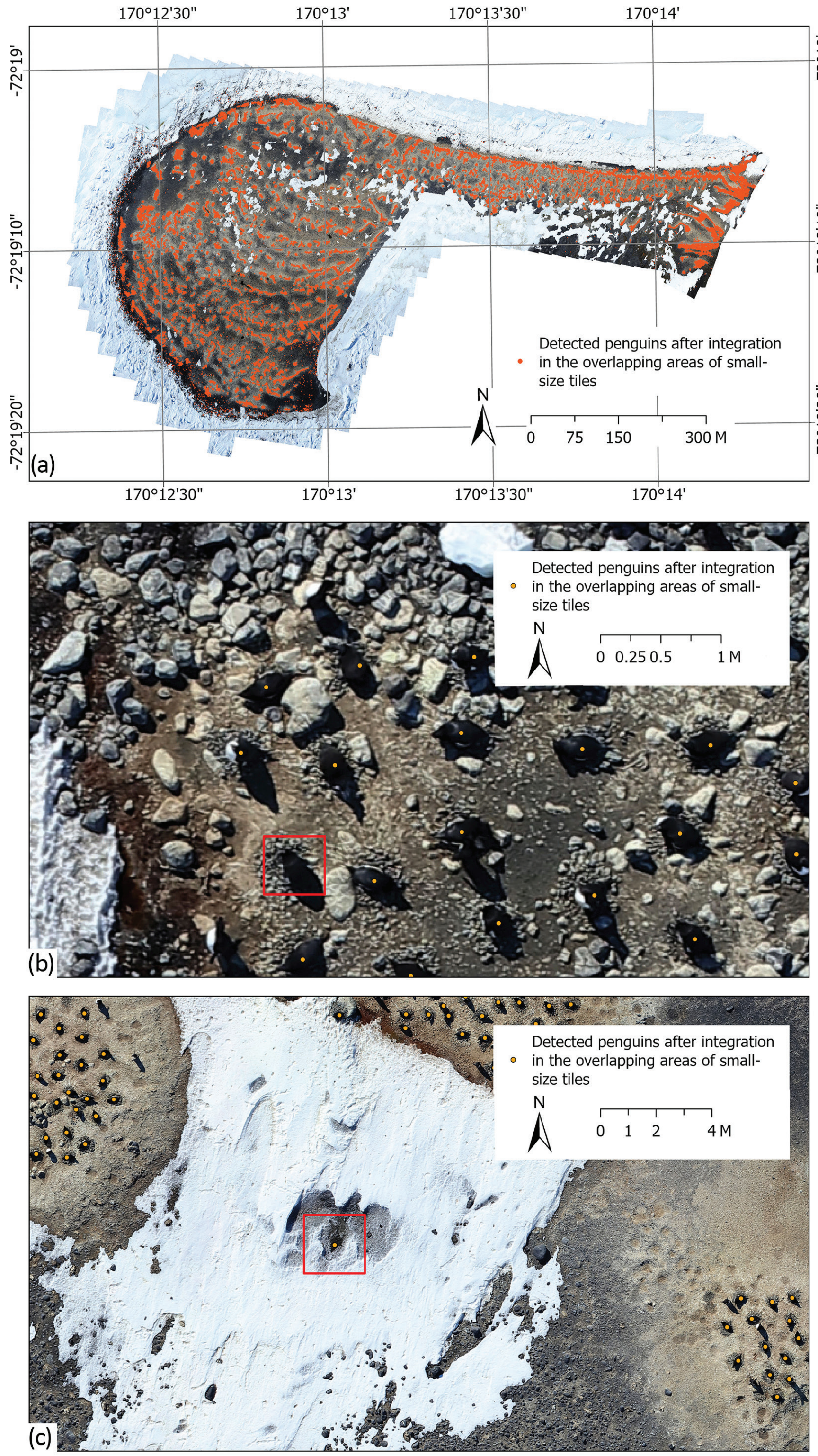

Fig. 7 Detection results for nesting Adélie penguins across the entire Cape Hallett area: (a) points marking nesting Adélie penguins across the Cape Hallett area; (b) an example of undetected penguins with non-typical posture on dark land highlighted in a red box; and (c) an example of a wet area incorrectly identified as a nesting penguin highlighted in a red box.

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long-term monitoring framework. This monitoring protocol has been applied across multiple years, ensuring internal consistency and interannual comparability. Accordingly, in this study, the aerial survey results are treated as an external reference data set rather than as a pixel-level ground truth with explicitly quantified uncertainty. The comparison was assessed using counting accuracy, a metric that quantifies the precision of a count by measuring the deviation between the estimated and actual numbers (Wu et al. 2023). This evaluation, designed to determine the reliability of the nesting penguin count, resulted in a counting accuracy of 97.5%, indicating strong agreement between the two counts and suggesting that the automated YOLOv11-based detection approach can effectively complement traditional manual counting methods.

$$\text{counting accuracy} = 1 - \frac{\left|Pred_{\text{num}} - Ref_{\text{num}}\right|}{Ref_{\text{num}}}, \qquad \text{Eqn. 1}$$

where $Pred_{\text{num}}$ and Ref_{num} denote the detection and reference counts, respectively.

Discussion

This study evaluated the performance of the YOLOv11 detection model in a single-species colony of Adélie penguins. This approach allows for a rigorous assessment of model performance under controlled single-species colony conditions, while avoiding confounding effects associated with interspecific variation in morphology, posture, plumage characteristics and nesting behaviour. However, in many Antarctic coastal regions, Adélie, gentoo and chinstrap penguins occur in close proximity or form mixed colonies (Wethington et al. 2023), where automated detection and species discrimination are inherently more challenging. In such environments, differences in body size, visual contrast, nesting density and spatial overlap may reduce detection accuracy and increase the likelihood of cross-species misclassification. Consequently, the performance demonstrated in the present single-species setting should not be directly generalized to mixed-species colonies without additional validation.

Therefore, future research needs explicitly evaluating the applicability of YOLOv11-based detection frameworks in mixed-species environments. This will require the development of multi-class detection models, species-specific annotation strategies and systematic assessment of cross-species confusion errors, alongside evaluation of both detection and classification performance. In this context, the VHR drone imagery offers a potential advantage over traditional high-altitude aerial surveys conducted under CCAMLR Standard Method A3B which rely on high-altitude (above 2000 feet above ground level) crewed aircraft and manual interpretation, as drone-based observations enable finer-scale discrimination of individual penguins and nests, improved separation of overlapping individuals and more reliable extraction of species-level features. Accordingly, the present study can be viewed as a foundational step towards extending deep learning-based monitoring approaches to more complex ecological settings, rather than as a fully validated solution for mixed-species colony monitoring.

Despite the detection performance achieved in this study, several limitations should be acknowledged and suggest directions for future research. The model was trained and evaluated using UAV imagery acquired from a single colony and a single breeding season, which may constrain the generalizability of the results to other sites or temporal contexts. Consequently, validation across multiple colonies and breeding seasons will be necessary to evaluate the robustness of the proposed approach under diverse ecological and environmental conditions. In addition, the use of RGB imagery alone makes detection performance sensitive to illumination variability and low-contrast background conditions, indicating that the incorporation of multimodal data, such as thermal or multispectral imagery (Bird et al. 2020; Hinke et al. 2022), may improve detection reliability. Finally, although high precision and recall indicate strong colony-wide counting performance, quantification of uncertainty (Sharifuzzaman et al. 2024) associated with automated population estimates remains an important consideration for ecological applications and should be addressed in future studies.

Conclusion

In this study, we applied state-of-the-art deep learning-based object detection techniques and drone images to conduct a census of nesting Adélie penguins on Cape Hallett, on the Ross Sea, estimating a population of 47 340 nesting Adélie penguins. Using the YOLOv11 nesting Adélie penguin detection model, this study demonstrated the ability to efficiently process large data sets of drone imagery, achieving scalability and low-disturbance monitoring in remote and challenging Antarctic environments. The performance of the YOLOv11 model highlights its potential for detection and counting penguins with minimal human intervention, significantly reducing logistical complexity and disturbances to wildlife. Minor challenges were noted, such as false detections caused by rocks, shadows and wet areas resembling penguins, as well as missed detections in atypical nesting areas (e.g., dark land regions lacking reddish guano). The approach demonstrated computational scalability for colony-wide processing of VHR drone imagery at the study site. Regional transferability across the Ross Sea remains to be established through multi-colony and multi-season validation.

The application of the VHR drone imagery-based YOLOv11 framework is not limited to producing population estimates comparable to those obtained from traditional aerial surveys but also encompasses several potential operational and methodological advantages. These can include relatively lower operational costs and logistical demands compared to crewed aircraft-based surveys, higher spatial resolution and the capacity for automated processing of large image data sets. Collectively, these characteristics suggest that the proposed approach has the potential to be applied to repeated or longer-term monitoring of penguin colonies within the Ross Sea region.

These results underscore the value of integrating drone-based monitoring with deep learning-based object detection models as a useful tool for Antarctic conservation and ecosystem management. This approach facilitates long-term, efficient monitoring of Adélie penguin colonies and provides data for assessing the impacts of climate change and human activities. Future research should focus on enhancing the detection accuracy in complex or low-contrast habitats by refining detection algorithms and incorporating multispectral or thermal imaging. Expanding this methodology to other Adélie penguin colonies across the Ross Sea region will further support ecosystem-based management and evaluation of MPAs and strengthen efforts to preserve Antarctic biodiversity under rapidly changing environmental conditions.

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Disclosure statement

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