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Species classification of Antarctic pack-ice seals using very high-resolution imagery

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Abstract

We introduce a semiautomated machine learning method that employs high-resolution imagery for the species-level classification of Antarctic pack-ice seals. By incorporating the spatial distribution of hauled-out seals on ice into our analytical framework, we significantly enhance the accuracy of species identification. Employing a Random Forest model, we achieved 97.4% accuracy for crabeater seals and 98.0% for Weddell seals. To further refine our classification, we included three linearity measures: mean distance to a group's regression line, straightness index, and sinuosity index. Additional variables, such as the number of neighboring seals within a 250 m radius and distance of individual seals to the sea ice edge, also contributed to improved accuracy. Our study marks a significant advancement in the development of a cost-effective, unified Antarctic seal monitoring system, enhancing our understanding of seal spatial behavior and enabling more effective population tracking amid environmental changes.

KEYWORDS

Antarctic pack-ice seals, Random Forest, Ripley's K, spatial ecology, species identification, very high-resolution imagery

1 | INTRODUCTION

As marine predators, pack-ice seals represent a major component of the Southern Ocean (SO) ecosystem. Four species of seals belonging to the family Phocidae, the crabeater (*Lobodon carcinophaga*), Weddell (*Leptonychotes weddellii*), leopard (*Hydrurga leptonyx*) and Ross (*Omnatophoca rossi*) seal, have circumpolar distributions throughout

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the sea ice bearing waters surrounding the Antarctic continent. This sea ice habitat is critically important to seals, offering them a platform to rest, reproduce, give birth, and nurse their young, while also providing access to abundant food sources such as krill (Hückstädt et al., 2012; Reiss et al., 2017) and a refuge from predators (Costa & Crocker, 1996; Siniff, 1981).

Substantial effort has been expended in estimating the population sizes of the four species of pack-ice seals; however, the abundance estimates remain highly uncertain, varying across multiple orders of magnitude depending on the species considered (Bengtson, 2009; Bester et al., 2017; Erickson & Hanson, 1990; LaRue et al., 2021; Southwell et al., 2012). Despite uncertainty surrounding fundamental biological and population parameters, the influence of pack-ice seals on SO ecosystem structure and functioning are undeniable (Forcada et al., 2008). In the region separating the waters of the Weddell Sea from those of the Scotia Sea (i.e., the Weddell-Scotia confluence zone) alone, crabeater seals are thought to consume more Antarctic krill than all other krill-dependent predators combined, including whales and penguins (Forcada et al., 2008). Recent evidence suggests that these seals may face increased competition for this critical food source due to the spatial overlap between critical seal habitats and growing krill fishing operations (Forcada et al., 2012; Hinke et al., 2017). Specifically, studies have found significant spatial overlap between areas that are heavily fished for krill and the regions where seals typically forage, thereby increasing the likelihood of direct competition for this key resource (Forcada et al., 2012; Hinke et al., 2017). The scale of krill fishing in these overlapping areas further exacerbates the competition, posing potential threats to the seals' food security. Furthermore, the cumulative effects of climate change, sea ice loss, and krill fishing are likely to negatively impact krill abundance, thereby posing threats to krill-dependent predators like seals (Flores et al., 2012; Hofman, 2016).

The capabilities provided by modern remote sensing platforms represent a significant advancement in our ability to monitor wildlife populations over large geographic areas. Very high-resolution (VHR) imagery offers a noninvasive and cost-effective alternative to traditional wildlife surveys, allowing for monitoring at much larger spatial scales than is possible through traditional methods (Fretwell et al., 2012; LaRue et al., 2011; Lynch & LaRue, 2014). Early studies that employed satellite imagery to study pack-ice seal biology largely relied on manual annotation by experts or trained volunteers (LaRue et al., 2011; Wege et al., 2020). While these studies provided valuable insight into seal abundance and spatial distribution, manually annotating pack-ice seals in VHR imagery is extremely laborious and challenged by variations in lighting, substrate conditions, and postprocessing artifacts (Gonçalves et al., 2020). More recently, the use of deep learning and computer vision methods has enabled researchers to identify seals across whole imagery catalogs in an automated manner (Gonçalves et al., 2020, 2022). The development of methodology to automatically detect seals from VHR imagery have allowed researchers to quickly process the large amount of imagery gathered over the Southern Ocean, providing a platform for comprehensive continental-scale survey campaigns.

The distinctive behavior of hauling out, whereby seals move onto ice floes, is shared by all pack-ice seals, and enables us to detect seals from VHR imagery. While we can identify pack-ice seals at scale using VHR imagery, the spatial resolution of these collections is not sufficient for direct species identification (Figure 1). Previous studies have largely relied on habitat and species-specific habitat preferences to differentiate among seal species, presuming that seals on fast ice were predominately Weddell seals (LaRue et al., 2011) and seals in the pack-ice would be mainly crabeater seals (Wege et al., 2020). However, using sea ice habitat alone as an indicator of species does not permit inference on species identification in areas where multiple species (e.g., Weddell and crabeater seals) coexist, requiring the use of other methods to accomplish the task.

Here we present a semiautomated analysis that uses machine learning methods to infer species identification in VHR imagery. We leverage both the habitat characteristics (e.g., sea ice type) and spatial dynamics of groups of hauled-out seals to assign a likely species group assignment. We focused on classifying seal groups as either crabeater or Weddell seals since these two species are significantly more abundant than either Ross or leopard seals and because we can use training data in areas where one or the other is known to predominate (Erickson & Hanson, 1990; LaRue et al., 2021; Laws, 1977). By leveraging differences in spatial patterning (e.g., seal group size,

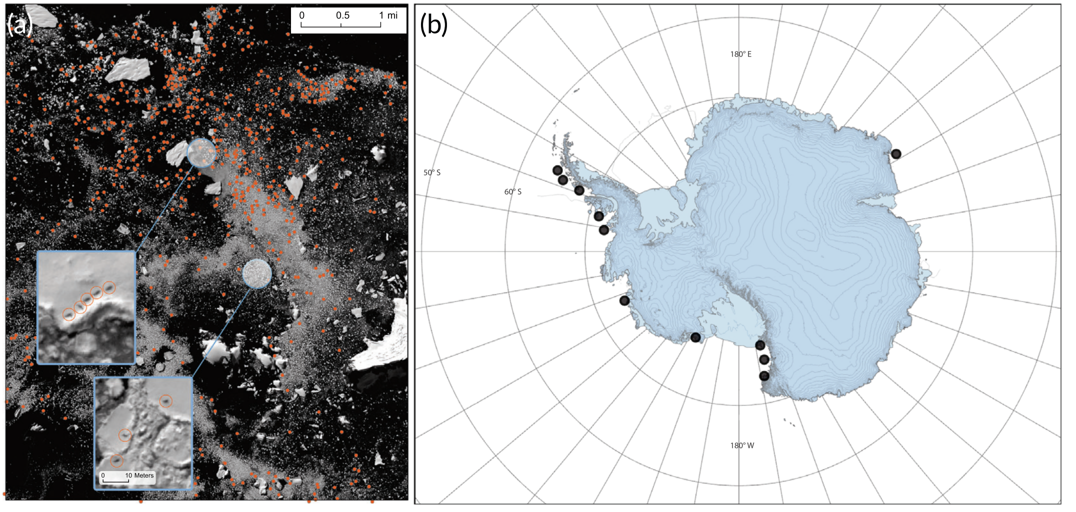

FIGURE 1 (a) Example of individual seals on ice floes (pink circles have been overlaid on each seal in the image). Inset image illustrates the challenge of assigning individual seals to a given species due to the inadequate spatial resolution. (b) Locations of imagery used in this study. Figure created using ESRI ArcGIS Pro 3.0 (https://pro.arcgis.com). Imagery © 2023 Maxar NextView License.

interindividual distance, spatial arrangement, and distance to ice edge) within seal groups hauled out on sea ice during the breeding season, our work fills a key requirement for the eventual use of satellite imagery for pan-Antarctic seal population estimates.

2 | METHODS

2.1 | Satellite imagery

We used VHR panchromatic images (each referred to as a "scene") of the Antarctic coast (Figure 1, Table 1) acquired by Maxar's Worldview Legion constellation (Maxar, 2019; https://www.maxar.com/constellation), with on-nadir resolution ranging from 0.31 m/pixel to 0.50 m/pixel with individual image footprints ranging from 172 km^2 (Worldview-3) to 303 km^2 (Worldview-1). The majority of scenes used in this study were previously identified as containing pack-ice seals by an automated Convolutional Neural Network (CNN) detection model (SealNet 2.0), previously developed for the purpose of identifying pack-ice seals in Worldview-3 imagery (Gonçalves et al., 2020). In addition, we used three scenes in Erebus Bay that were identified by LaRue et al. (2011) as containing Weddell seals (Figure 2). LaRue confirmed that the seals identified in the imagery were indeed Weddell seals, based on their location at long-studied breeding locations. This validation served to ground truth our classification methods, ensuring the accuracy of our VHR techniques for detecting this species.

2.2 | Aerial imagery

In addition to high-resolution satellite images, we also used aerial imagery captured during NASA's Operation Icebridge campaign (Neumann et al., 2019). We used the DMS Level-1B Geolocated and Orthorectified Imagery data set. The DMS airborne digital camera acquires high-resolution color and panchromatic imagery, with spatial resolution ranging from 0.015 m/pixel to 0.25 m/pixel on-nadir depending on flight altitude. DMS image Geotiffs were

TABLE 1 Satellite images used in this study.

Scene ID	Platform	Resolution	Region	Putative species	Scene area (km^2)
1040010027CB7300	Worldview-3	0.31	East Antarctica	Weddell	172
10100100CA19000	QuickBird-2	0.60	Ross Sea	Weddell	272
103001004ACAE600	Worldview-2	0.46	Ross Sea	Weddell	269
10200100180FFB00	Worldview-2	0.46	Ross Sea	Weddell	269
1040010063C99900	Worldview-3	0.31	Ross Sea	Weddell	172
101001000E793C00	QuickBird-2	0.60	Ross Sea	Weddell	272
10400100196BE200	Worldview-3	0.31	West Antarctic Peninsula	Crabeater	172
1040010058220800	Worldview-3	0.31	West Antarctic Peninsula	Crabeater	172
10400100569DCD00	Worldview-3	0.31	West Antarctic Peninsula	Weddell	172
104010016401600	Worldview-3	0.31	West Antarctic Peninsula	Crabeater	172
10400100562FC100	Worldview-3	0.31	West Antarctic Peninsula	Crabeater	172

downloaded directly from the NASA Distributed Active Archive Center (DAAC) at the National Snow and Ice Data Center (NSIDC). Due to the significant time required for manual search of aerial imagery, we concentrated our efforts on two specific subregions: Marguerite Bay (66.7°S–69.7°S) along the Western Antarctic Peninsula, and the Eastern Ross Sea (72°S–77°S). We selected these locations because they have been identified as areas with a high concentration of pack-ice seals (Burns et al., 2008; Friedlaender et al., 2011). In these two areas we searched 60 discrete flight survey tracks made up of 10,000 individual but overlapping DMS images. We normalized images for color and brightness to aid in their interpretation and images along each flight path were merged into orthomosaics. Further details on image processing and seal annotation are included in the Supplemental Materials.

2.3 | Sea ice feature extraction

Antarctic pack-ice seals haul out on a variety of sea ice environments. To characterize and extract pack-ice (free floating sea ice) and fast-ice (sea ice "fastened" to the continent) environmental features, we segmented individual image scenes using the CNN pipeline developed in Gonçalves et al. (2022). Features identified by the CNN segmentation as sea ice were automatically extracted as geospatial polygon features and exported as an GeoJSON layer, with geographic coordinate information appended to each ice floe (Figure 3). Quality and accuracy of each sea ice feature extraction was assessed visually, and erroneous extractions were manually corrected. In scenes dominated by fast-ice, we manually digitized geospatial polygons to represent individual sea ice leads and open water features. These polygons were then extracted and saved as scene-specific GeoJSON files.

2.4 | Seal location annotations

The satellite imagery data sets used in this study were extracted from a set of 11 panchromatic images (Table 1) covering 2,524 km^2 that: (1) were of sufficient image quality (i.e., cloud free, low shadow incidence) and (2) captured the

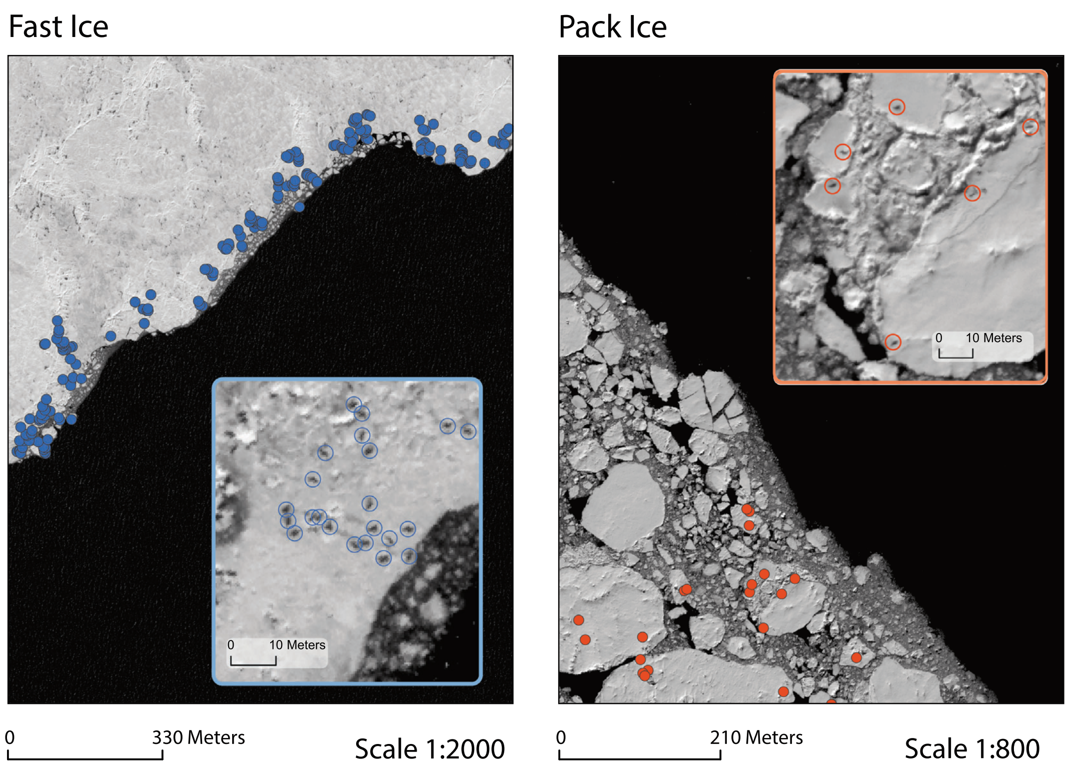

FIGURE 2 Seals identified in a satellite image scene (© 2023 Maxar NextView License) in an area dominated by Weddell seals (blue circles) and in an area dominated by crabeater seals (orange circles). Figure created using ESRI ArcGIS Pro 3.0 (https://pro.arcgis.com).

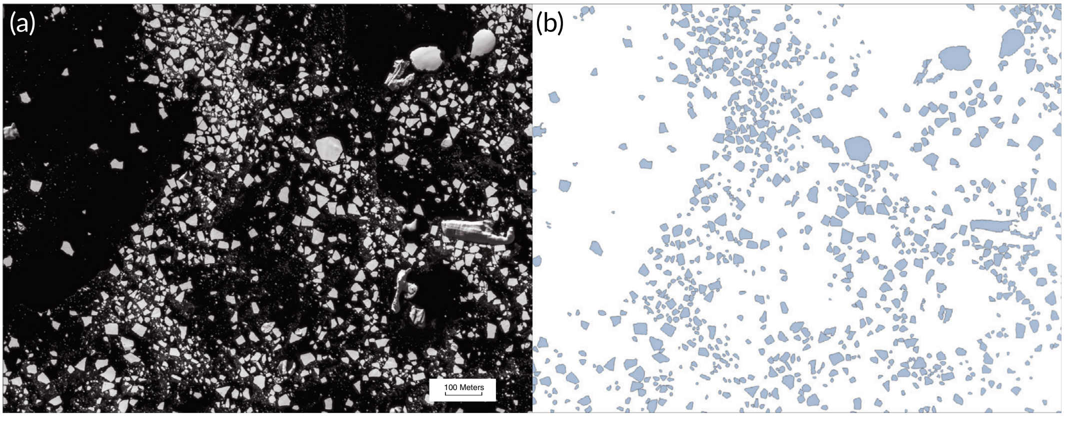

FIGURE 3 (a) Example of sea ice landscape in Worldview-3 imagery (© 2021 Maxar NextView License); (b) Sea ice polygons generated from source imagery. Figure created using ESRI ArcGIS Pro 3.0 (https://pro.arcgis.com).

entirety of a haul-out location within the image. The annotation process involved both satellite and aerial imagery data sets and was carried out by two skilled remote sensing analysts (M.W. and E.T.). Where CNN annotations were not available, we manually inspected the imagery of the Antarctic coast using a systematic grid-search method. We conducted the inspection at a scale where individual seals were detectable. We appended a geolocated spatial point to a GIS (geographic information system) spatial point database at the centroid of each putative seal found to mark its location. We employed an independent double-observer approach, retaining only the putative seal locations identified by both observers, to construct a single consensus data set.

After annotating putative seal locations, extracting sea ice features, and calculating spatial covariates (e.g., nearest- neighbor, distance, group size, etc.) in both the satellite and aerial imagery, we consolidated all GeoJSON data sets into a single geodatabase. Due to the substantial difference in spatial resolution between satellite and aerial images, the total number of identifiable seals can range from tens of individuals in a single aerial image to thousands of individuals in a single satellite image.

2.5 | Spatial clustering analysis

For the purpose of exploratory analysis, we tested for clustering in the spatial distribution of seals found on fast-ice versus seals found on free-floating pack-ice using Ripley's K statistic (Ripley, 1976). Ripley's K is a second-order (covariance of distances) function used to test for clustering and dispersion in spatial point patterns (Ripley, 1976) over a range of interpoint distances (Figure 4). By examining K(r) at various spatial scales (e.g., ice floe, pupping colony, region, etc.), it is possible to identify distances at which individuals occur more often than would be expected under complete spatial randomness (CSR). The K(r) function is given by

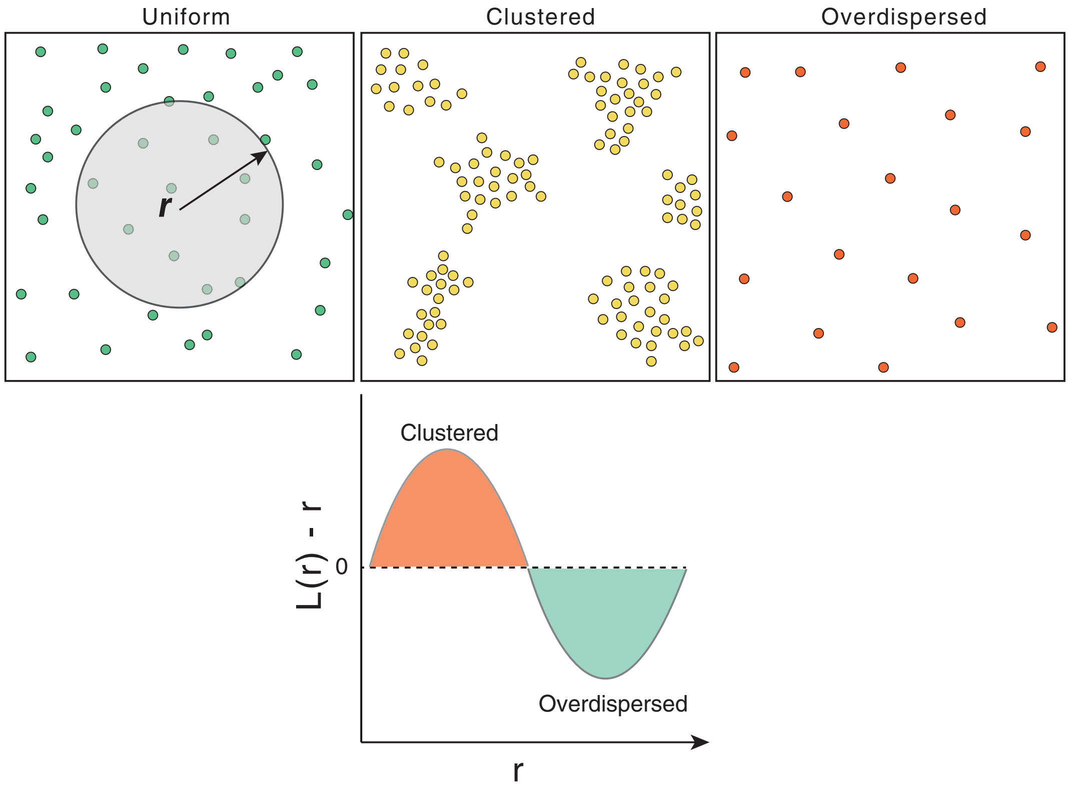

FIGURE 4 Example point patterns illustrating spatially random, clustered, and overdispersed point patterns. L(r)-r = 0 indicates complete spatial randomness (CSR), values above and below zero indicate spatial clustering and dispersion, respectively. Figure created in Adobe Illustrator 27.2 (https://www.adobe.com/products/illustrator.html).

$$K(r) = \frac{1}{\lambda} \sum_{i} \sum_{j \neq i} \frac{I(d_{ij} \le r)}{N} \tag{1}$$

where $I(d_{ij} \le r)$ is an indicator function that takes the value 1 each time the distance between points i and j is less than or equal to the radius r, λ is the average density of points per unit area, and *N* is the total number of points in the pattern being considered. The expected value of K(r) for a random (Poisson) distribution is πr^2 and the deviations from this expectation indicates the scales of clustering and dispersion (Kiskowski et al., 2009).

In practice, we used a scaled and centered version of Ripley's K known as Besag's L(r) function (Besag, 1974):

$$L(r) = \sqrt{\frac{K(r)}{\pi} - r} \tag{2}$$

whose expected value is 0 for complete spatial randomness. L(r) > 0 indicates that the observed distribution of point locations (i.e., seals) is clustered, while L(r) < 0 suggests spatial dispersion. The statistical significance of the observed L(r) hinges on an estimate of the variance for CSR, as observations falling outside this confidence interval would be considered statistically significant. Because the spatial patterning of sea ice habitat can result in clustering that is independent of the seals' spatial distribution among ice pans used as haul-outs, we limited the spatial domain for generating points under CSR to sea ice features visible in the imagery. We also matched the number of CSR points generated to the number of seals observed in each scene. In other words, the null distribution (which is generated for each scene) is complete spatial randomness within the observed sea ice domain and significant clustering would represent aggregation above and beyond that imposed by the patchiness of the ice floes. For each simulated CSR pattern, we calculated L(r) and used the 2.5th and 97.5th percentiles at each radius to form the lower and upper confidence intervals for that specific scene. In this way, each scene was associated with an observed L(r) and a confidence interval that represents the expected value of L(r) if seals were randomly located within the available sea ice habitat in that specific scene. To calculate an average L(r) for each species, we averaged the observed L(r) curves for each scene. L(r) estimates for individual scenes are provided in Figures S1–S9. We used these results to identify potential radii that might aid in discriminating between species in our RF Classification model.

2.6 | Exploratory analyses for species differences

As an initial exploratory analysis, we conducted *t* tests on 21 predictor variables to identify any significant differences between crabeater seals and Weddell seals. The study covariates include several measures to assess the group size and clustering of individual seals within haul-out areas, the distance to open water features (e.g., ice floe edge or open water lead), and three measures of spatial orientation (see Figure 5). A seal "group" was defined as a collection of individuals each within 25 m of another group member, and group size was defined as the total number of individuals within that cluster. In addition to the number of individuals within the group, we included group size, the distance to a seal's nearest-neighbor and the number of seals encompassed within distances ranging from 10 to 800 m (see Supplemental Materials B1). Three measures of spatial configuration were calculated to investigate fine-scale differences in seal group arrangement. These "linearity" measures included: (1) the mean distance of each seal to the standardized-major axis regression line for the group (e.g., the R^2 index); (2) a straightness index for each seal group; and (3) a sinuosity index for each seal group following (Benhamou, 2004). The code required to calculate each measure is included in the Supplemental Materials.

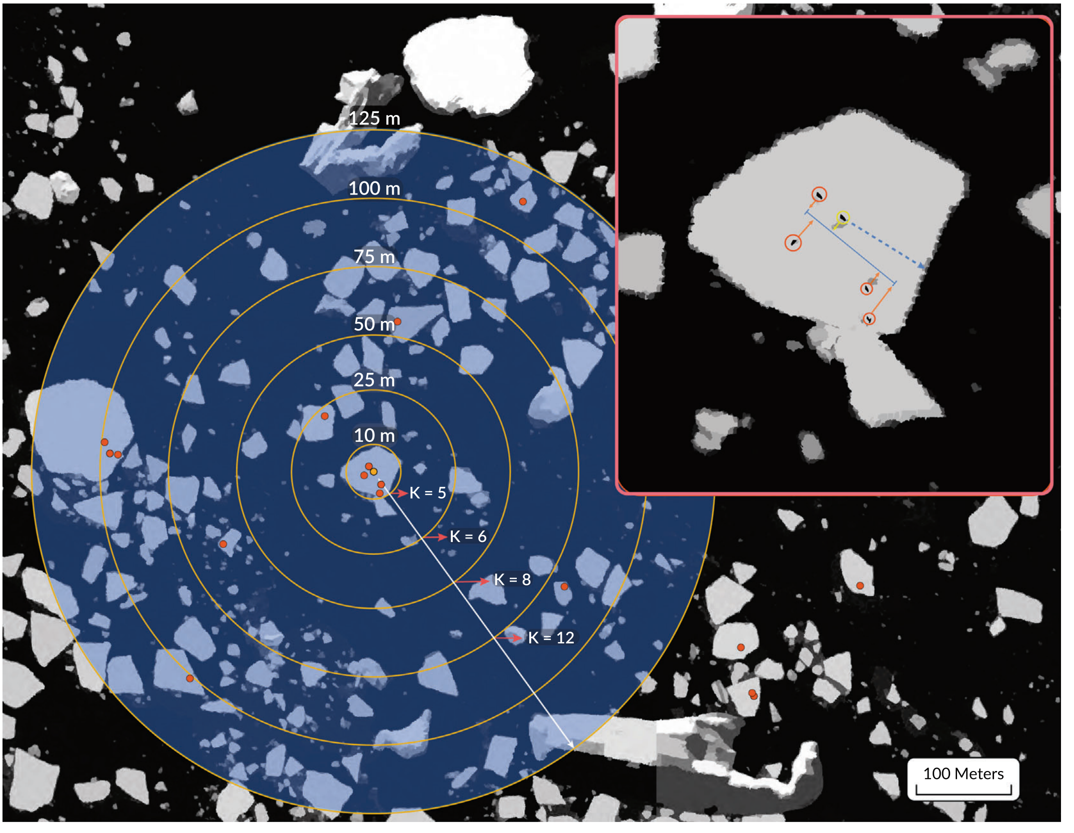

FIGURE 5 This diagram illustrates the spatial covariates used in this study. Circular windows indicate neighborhood search fields used to estimate the number of pack-ice seals (K) relative to the target seal (orange) for each predetermined search radius. The inset shows the estimation of linearity measures for a local group of pack-ice seals. Figure created using ESRI ArcGIS Pro.
3.0 (https://pro.arcgis.com)

2.7 | Variable correlation analysis

We conducted a correlation analysis as part of our exploratory data analysis to explore the relationships among various spatial covariates in our seal location data set (see Figure S1). Notably, the number of neighboring seals within a range of 10–800 m displayed high levels of intercorrelation, often with coefficients exceeding 0.9. This is expected as each metric is effectively a superset of the previous, smaller-radius metric, naturally sharing significant information about seal proximity. In contrast, the straightness index exhibited negative correlations with most other spatial covariates, suggesting it captures unique aspects of spatial variability not captured by metrics such as neighborhood seal count. Similarly, the R^2 index from the SMA regression, which serves as a measure of linearity in seal group arrangements, displayed low correlations with other predictors. This indicates that it provides a unique contribution to the model, specifically in quantifying the linearity or nonlinearity in the spatial configurations of seal groups. The sinuosity index also displayed low correlations with other predictors, underscoring its unique role in capturing finer intragroup variations.

To better understand the underlying structure of our data set, we employed Principal Component Analysis (PCA). Our results, as detailed in Figure S2 and Table S1, indicate that the first two principal components explain roughly 78% of the overall variance. Despite this high level of explained variance, we chose to retain all original variables for our predictive modeling. This decision was based on our use of a conditional inference variant of the Random Forest (RF) algorithm. Known for its robustness to multicollinearity and high-dimensionality (Strobl et al., 2008), this variant employs an ensemble-based approach and an unbiased variable selection mechanism. These features ensure effective handling of complex interactions among variables, even in the presence of multicollinearity. Therefore, we proceeded with the complete set of variables to fully leverage the algorithm's ability to capture the intricacies of our data set.

2.8 | Random Forest classification models

We leveraged a RF model (Breiman, 2001; Cutler et al., 2007) to predict species-level classification for hauled-out Weddell and crabeater seals. RF is an ensemble learning method that addresses common issues with traditional decision trees such as over-fitting (Breiman, 2001; Cutler et al., 2007) and can provide more reliable predictions in data sets with many independent variables (Cutler et al., 2007). RF models have several hyperparameters that can be adjusted for improved performance, including *ntree* and *mtry*, which control the structure and size of the forest, respectively.

We used the conditional inference variant of RF as it is especially suitable for data sets with highly correlated variables due to its robustness in calculating variable importance and its capacity to generate more accurate outcomes (Strobl et al., 2009). Compared to the original version of RF, conditional inference random forests employ conditional inference trees as base learners instead of classification and regression trees and use an unbiased subsampling without replacement scheme instead of bootstrapping. RF models in this study were implemented in the R programming language using the *cForest* function from the Party package (Strobl et al., 2009; R Core Team, 2021). We chose *ntree* and *mtry* to maximize classification accuracy, and report accuracy as the percentage of seals for which the category of seal was predicted correctly. We employed a grid search approach with cross-validation to determine the optimal *ntree* and *mtry* parameters.

We developed two distinct RF models, both of which are based on individual seals detected in our imagery data sets. The first model, which includes linearity metrics, encompasses 3,012 individual seal observations and focuses on seal groups with a minimum of three seals. This is the smallest group size that allows for a reliable calculation of linearity metrics. The second model, which excludes linearity metrics, considers a broader data set with 5,477 individual seal observations. For each model, we constructed 2,500 conditional classification trees using the species of each individual seal—either Weddell or crabeater—as the response variable. The model without linearity metrics used 21 predictor variables and incorporated all 5,477 individual seal locations. In contrast, the model with linearity metrics applied 19 predictor variables across its 3,012 individual seal locations. To assess the models' accuracy, we employed Out-of-Bag (OOB) samples during training, thereby negating the need for separate training and test data sets.

2.8.1 | Hyperparameter tuning

To identify optimal hyperparameter values for each RF model, a grid search approach with k-fold cross-validation was performed using the Caret package (Kuhn, 2012) in R (R Core Team, 2021), and k was set to 5. Upper bound values of *ntree* and *mtry* were set to 5,000 and 10, respectively.

2.8.2 | Variable importance

RF variable importance measures the influence of potential predictor variables on the response variable, offering an advantage over univariate screening methods by accounting for the effect of each predictor variable independently and in conjunction with other predictors (Strobl et al., 2008). We used RF Conditional Permutation Feature Importance described by Strobl et al. (2008), which works by rearranging each feature within groups of observations with similar values for the other predictor variables and therefore maintains the correlation structure between the feature and the other predictor variables.

Despite being more computationally intensive than other feature importance metrics (e.g., Gini Impurity, permutation feature importance), Conditional Permutation Feature Importance provides several distinct advantages: (1) it provides more reliable and accurate feature importance scores than other measures, as it takes into account interactions among features; (2) it can measure the importance of individual features, whereas metrics like Gini importance only measure the importance of a feature relative to the other features; (3) it is considered more robust to correlated features; and (4) it is more easily interpreted than Gini importance because feature importance is measured in terms of the actual change in accuracy (Altman, 1992; Breiman, 2001; Hastie et al., 2009; Strobl et al., 2008).

2.8.3 | Model accuracy assessment

To assess the performance of our RF models, we employed Out-of-Bag (OOB) samples during the training phase using the entire data set. Unlike typical approaches that set aside a separate test data set, our evaluation incorporates 100% of the available seal locations, providing a way to estimate model performance without requiring a separate test set.

We selected a comprehensive suite of eight performance metrics for our assessment: Kappa, accuracy, precision, recall (sensitivity), F1 score, the area under the Receiver Operating Characteristic (ROC) curve (AUC), and specificity. Each metric provides distinct insights into the model's performance. Kappa, for instance, accounts for chance agreement to offer a robust measure of model accuracy. It ranges from -1 to 1, where 0 represents agreement due to chance and 1 signifies perfect agreement (Carletta, 1996). In the context of our RF models, a Kappa value of 1 would imply that the model perfectly distinguishes between crabeater seals and Weddell seals, achieving flawless classification without any errors. We use accuracy to quantify the overall percentage of correctly classified observations, offering a general gauge of how well the model performs. Precision and recall specifically address the model's capability to correctly identify true positives. Precision calculates the proportion of true positives among the predicted positives, while recall identifies the proportion of true positives that the model correctly classifies. The F1 score balances the trade-offs between precision and sensitivity by taking their harmonic mean. Finally, the area under the ROC curve (AUC) gives an aggregate measure of the model's performance across various classification thresholds. Specificity measures the model's ability to correctly identify true negatives. Together, these metrics offer a multifaceted evaluation of the model, capturing not just overall accuracy but also its generalizability to new, unseen data.

3 | RESULTS

3.1 | Spatial clustering analysis results

Averaged across all image scenes used in this study, we found significant clustering among both crabeater and Weddell seals throughout the range of their study areas with L(r) exceeding the distribution under the null hypothesis of CSR beyond a 5-m radius and remaining statistically significant out to 4 km (the largest radius considered; Figure 6).

The size of the imagery generates a boundary effect that precludes looking at clustering at larger spatial scales. The range of scene sizes in our study varied from 13.1 $\times$ 13.1 km to 16.7 $\times$ 16.7 km, providing context

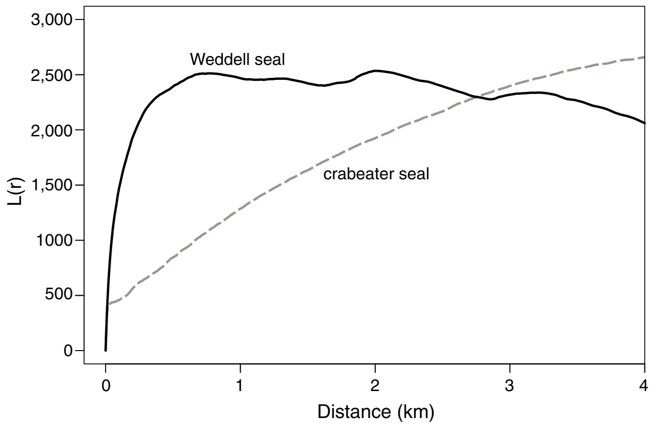

FIGURE 6 Average L(r) estimates for seals in crabeater-dominated and Weddell-dominated scenes. Confidence intervals were calculated per scene and for clarity are not shown in this figure but at all radii, the curves shown fall outside the confidence intervals for CSR. Figure created in Adobe Illustrator 27.2 (https://www.adobe.com/products/illustrator.html).

for the size of sea ice pans and floes used as haul-outs. The mean slope of L(r) across all scenes differed substantially between crabeater and Weddell seals (Figure 6), with crabeater seals exhibiting a rapid increase in L(r) up to a radius of 10 m, followed by a gradual incline until the extent of the image scene (4 km). Weddell seals, however, displayed a steep incline in L(r) until a radius of 250 m, then a more gradual increase until 800 m, the radius at which L(r) was most divergent, followed by a slow decline until the extent of the image scene, with local peaks in L(r) near 2 km.

Results from Bonferroni corrected *t* tests showed statistically significant differences in the mean values of 21 predictor variables (Table S3) between crabeater seals and Weddell seals, suggesting that seal species may be differentiable based on their spatial arrangement and orientation. Compared to crabeater seals, Weddell seals were more likely be observed in closer proximity to one another, hauled out on sea ice features in greater numbers (the average Weddell seal being in a group of 16 compared to <3 for crabeaters; Table S3), positioned themselves farther from open-water features (e.g., ice edge, sea ice leads), and arranged themselves with lower degrees of linearity.

3.2 | Random Forest model

Hyperparameter grid search and optimization identified 2,500 trees as the optimal number with only marginal improvements up to 3,000. The optimal *mtry* was 7, with different runs with varying *mtry* values (1–9) resulted in marginally poorer average classification accuracy (93.2% at $mtry = 1$, to 93.8% at $mtry = 9$).

The RF model that includes linearity metrics achieves an overall accuracy score of approximately 97.6%. It classifies 98.0% of Weddell seals and 97.4% of crabeater seals accurately (Figure 3, Table 2). According to Conditional Permutation Feature Importance, the most influential variables are (in descending order of importance) the straightness index, the SMA regression R^2 index, the sinuosity index, distance to the ice edge, and the total number of neighboring seals within a 250-m distance (Figure 7). On the other hand, the RF model without linearity metrics achieves an overall accuracy of about 93.4%. It correctly identifies 97.1% of Weddell seals and 91.5% of crabeater seals (Table 3). The most influential variables in this model include distance to the edge, the total number of neighboring seals within 250 and 800 m, group size, and nearest-neighbor distance (Figure 7).

TABLE 2 Validation of conditional inference random forest models. Various performance metrics are reported.

Model validation	RF - with linearity OOB	RF - without linearity OOB
Accuracy	0.976	0.934
Kappa	0.950	0.858
Precision	0.974	0.915
Recall (Sensitivity)	0.988	0.984
F1 Score	0.981	0.949
Specificity	0.959	0.855
AUC	0.973	0.920
OOB Error Rate	0.024	0.066
Proportion of all observations in data set	16%	30%

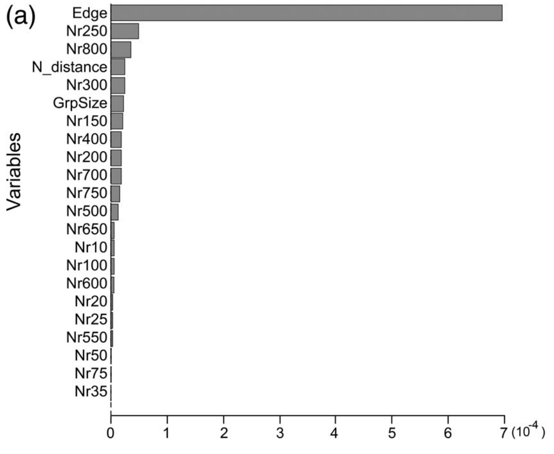

FIGURE 7 Variable importance using Conditional permutation importance. Variables are listed in descending order of importance. (a) Results for best fitting Random Forest model not including linearity calculations for seal groups. (b) Results for best fitting Random Forest model including linearity metrics for seal groups. Figure created using Adobe Illustrator. (https://www.adobe.com/products/illustrator.html).

TABLE 3 Seal group classification confusion matrix for Random Forest model not including linearity metrics for seal groups and Random Forest model including linearity metrics for seal groups.

	Predicted crabeater seals	Predicted Weddell seals
RF model not including linearity metrics		
Actual crabeater seals	3,312 (91.5%)	306 (8.5%)
Actual Weddell seals	53 (2.9%)	1,804 (97.1%)
RF model including linearity metrics		
Actual crabeater seals	3,323 (97.4%)	87 (2.6%)
Actual Weddell seals	42 (2.0%)	2,023 (98.0%)

4 | DISCUSSION

The importance of understanding the abundance of pack-ice seals to monitor Antarctic marine ecosystems is well known (Siniff, 1981, 1991), and their role as indicators of the SO ecosystem's health has encouraged several regional population surveys. Traditional field-based surveys, such as those conducted by helicopter or ship (Ackley et al., 2003; Bengtson et al., 2011; McLaren, 1966; Southwell et al., 2008), have provided a great deal of knowledge about pack-ice seals, yet their spatial and temporal coverage is usually restricted due to the difficulties of such work. The cost of field campaigns, shortage of personnel, and risk to observers further hamper the ability to obtain accurate and timely population estimates. This is particularly true in polar regions with highly remote areas that are difficult to access by most vessels due to seasonal darkness, cold temperatures, and sea ice coverage. Consequently, cost-effective survey methods for pack-ice seals were not available until the advent of satellite-based methods.

Cost-effective methods to identify and quantify seals at the species level are crucial. They would provide vital information on population status across the continent, including in regions occupied by both crabeater and Weddell seals, and are therefore essential for monitoring species and their responses to environmental change (Gonçalves et al., 2020; Siniff et al., 2008). In addition, they would enable a better understanding of the spatial dynamics of populations on a local scale, and also enable tracking the status and trends of populations that may be engaged in behaviors like temporary immigration or emigration exchanges (Cameron & Siniff, 2004; LaRue et al., 2011; Rotella et al., 2009). Therefore, the development of routine methods for identifying seal species across Antarctica is fundamental to our understanding of their ecology and to our capacity to assess the potential impacts of climate change or other human-induced influences. We developed a semiautomated machine learning analysis to identify groups of crabeater and Weddell seals in VHR imagery. Guided by the distinct spatial patterns of association that each species exhibits with conspecifics and visually identifiable sea ice features when hauled out, our approach revealed significant differences among all 21 predictor variables considered for these species. These findings suggest that it is possible to differentiate between crabeater and Weddell seal groups based on their spatial arrangement and physical orientation, even when the imagery resolution is insufficient for identifying individual seals by visual inspection.

Interestingly, Weddell seal groups were observed to locally cooccur in greater numbers and were arranged in closer proximity to one another, suggesting potential social or ecological drivers for such aggregations. Additionally, Weddell seals positioned themselves farther away from the water's edge and exhibited increased sinuosity in their group formations compared to crabeater seals. This is particularly noteworthy given that Weddell seals are often found along sea ice leads—cracks of open water surrounded by a mostly solid fast ice landscape—while crabeater seals are primarily observed on free-floating pack ice, comprising many individual but smaller floes. In the case of distance to the water's edge, the tendency of Weddell seals to position themselves farther away might reflect their preference for the more stable fast ice, possibly reducing predation risk or offering closer proximity to preferred feeding areas. Conversely, the more dynamic and fragmented pack ice environment frequented by crabeater seals may necessitate different spatial behaviors. The elevated sinuosity index implies that Weddell seal groups may adopt more intricate, nonlinear arrangements, possibly influenced by environmental variables or behavioral adaptations. In contrast, crabeater seals exhibited higher values on the straightness index and the SMA regression R^2 index, indicating a more linear and coordinated group arrangement. These patterns could be attributed to different behavioral drivers or environmental conditions affecting each species.

The relationship among the straightness Index, sinuosity Index, and the SMA regression R^2 index offers a comprehensive understanding of the spatial behaviors exhibited by different seal species. While the straightness index measures the degree of alignment within a group, the sinuosity index delves into finer details, revealing intragroup variations. Incorporating the SMA regression R^2 index adds an additional layer of statistical validation, helping to quantify the extent of linearity or nonlinearity in the spatial arrangements of seal groups.

By incorporating metrics of spatial arrangement—such as the straightness index, sinuosity index, and the SMA regression R^2 index—into our analysis, along with observations of local cooccurrence and relative proximity, we gain a more nuanced view of the spatial behaviors of different seal species. However, it is crucial to note that these metrics, derived from satellite imagery, capture only a single moment in what are undoubtedly dynamic behaviors and interactions. While the imagery provides valuable clues, its fixed nature imposes limitations on our ability to make strong inferences about the seals' behavioral ecology or social structures as they evolve through time.

The RF model that includes linearity metrics achieves high classification accuracy for both Weddell and crabeater seals, while the model without linearity metrics falls slightly shorter in accuracy at 97.1% and 91.5% correct identification for Weddell and crabeater seals, respectively. The addition of linearity metrics clearly improves the model's ability to differentiate between the two seal species. When we include linearity metrics, the most important factors for distinguishing between species groups are the straightness index, the SMA regression R^2 index, distance to edge, and the total number of neighboring seals within 250 m. Although not top-ranked by Conditional Permutation Feature importance, other metrics like seal group size and varying ranges of neighborhood seal density (e.g., total neighboring seals within 200–500 m) still enhance the model's differentiation capabilities between seal species.

Both RF models exhibited strong performance in classifying seal species from our testing data set. However, there were isolated instances where the model's classification diverged from our analysts' predictions, as shown in Figure 8. These discrepancies were relatively rare, with a misclassification rate of 6.5% ($n = 359$) for the RF model not incorporating linearity metrics, and 4.2% ($n = 129$) for the RF model that did incorporate linearity metrics. In both models, Weddell seals were more likely to be misclassified as crabeater seals, with rates of 8.5% ($n = 306$) for the

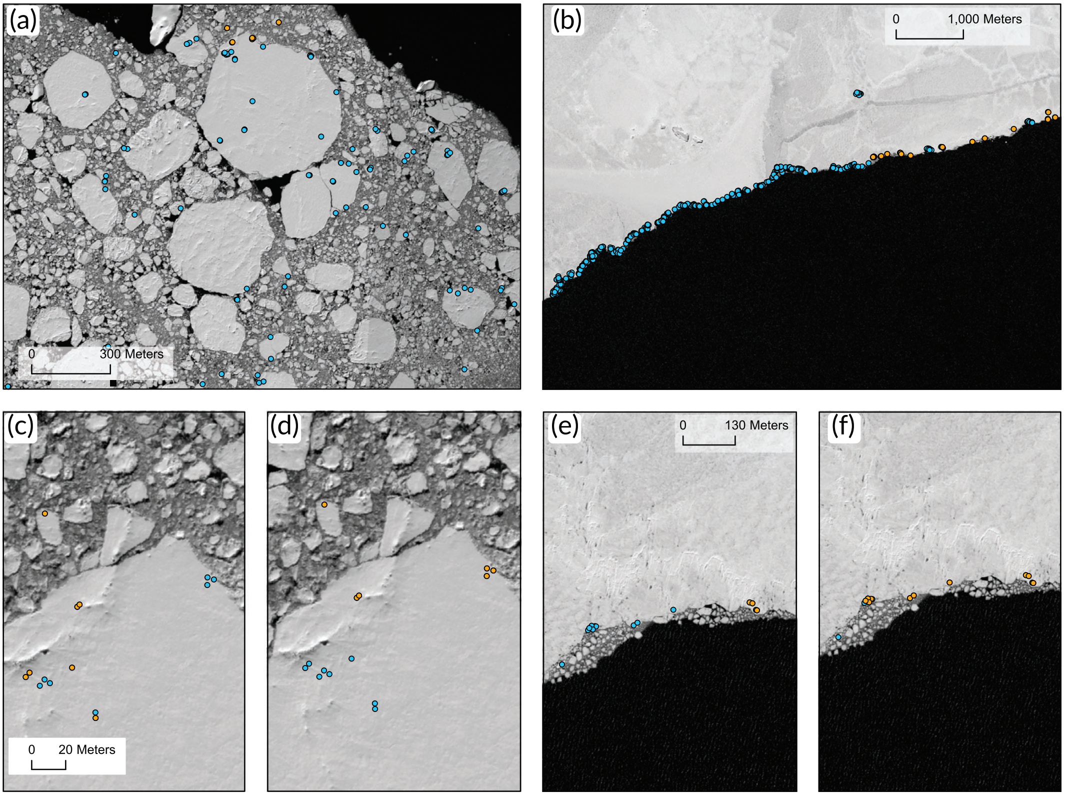

FIGURE 8 Examples of misclassification results. Panels (a) and (b) display the original annotation data, with the corresponding lower panels illustrating seals that were correctly classified (in blue) and misclassified (in orange). Panels (c) and (e) show classifications from the Random Forest model that incorporates linearity metrics, while Panels (d) and (f) present classifications from the Random Forest model without linearity metrics. This figure was created using ESRI ArcGIS Pro 3.0 (https://pro.arcgis.com).

model without linearity metrics and 2.5% ($n = 87$) for the model incorporating linearity metrics. Given the low frequency of these misclassifications, it is challenging to ascertain whether they stem from limitations in the model or annotation errors by the analysts (i.e., incorrectly labeling a seal's species). While misclassifications are commonplace in machine learning models, this finding emphasizes the importance of two elements: (1) augmenting the size and range of the training and validation data sets to evaluate the model's performance more comprehensively (Gonçalves et al. 2022); and (2) the complexity of creating and validating such models when direct, ground-truthing is either impossible or impractical.

This research represents a significant step forward in the development of a unified, cost-effective seal monitoring system for Antarctica. Algorithmic improvements and additional training data could further strengthen our analysis, especially if they are supplemented with data from ground-based observations. This would not only give us insight into the distribution and biology of seals, but also enable us to distinguish pack-ice seals by species from VHR images at scale, drastically increasing our capacity to analyze the effects of climate change-and anthropogenic activities such as industrial krill fishing.

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AUTHOR CONTRIBUTIONS

Michael Wethington: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; resources; software; supervision; validation; visualization; writing – original draft; writing – review and editing. **Bento Goncalves:** Data curation; methodology; resources; software; validation; writing – review and editing. **Emma Talis:** Data curation; investigation; validation; writing – review and editing. **Bilgecan Sen:** Formal analysis; methodology; validation; writing – review and editing. **Heather J Lynch:** Conceptualization; formal analysis; funding acquisition; methodology; supervision; writing – original draft; writing – review and editing.

Data Availability

All seal annotation data, code, and corresponding statistical analyses are included with this published article as a Supplementary Information file. Additional information may be obtained from the authors on request.

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SUPPORTING INFORMATION

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