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Through the Eyes of a Penguin: Estimating Krill Densities Using Animal-Borne Video Loggers

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June 2019

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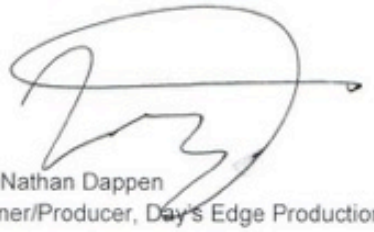

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Abstract

Antarctic krill (*Euphausia superba*) are a keystone species in the Southern Ocean and if their populations decline there could be detrimental impacts to many other species in the Antarctic ecosystem. In order to study krill, the National Oceanic and Atmospheric Administration (NOAA) regularly monitors the Antarctic ecosystem, including outfitting predators with cameras to record prey encounters during feeding events. NOAA also recently sponsored the development of an open-source underwater imagery analysis system called Video and Image Analytics for a Marine Environment (VIAME) in order to make automated methods to process mass amounts of underwater visual data accessible to analysts and non-computer scientists. The proposed work of this study will use the VIAME software to determine the volumetric densities of krill observed in a video recording during a chinstrap penguin foraging event from the 2018 field season. The methods developed by this study resulted in imaged volume based on the maximum resolvable range, counts of krill per volume, and subsequently densities of krill. These methods provide a basis for automatically processing and estimating densities of krill pursued and encountered by predators. Densities from the perspective of a predator have not been documented previously for the Antarctic ecosystem.

Introduction

Antarctic krill are a keystone species in the Southern Ocean. Declines or mass movements of krill populations have potential negative impacts to species that rely on krill for survival (Boopendranath 2013). Krill acts as the primary food source for different species of whales, seals, penguins, and fish in the Antarctic (Everson 2000, Hill et al. 2012). Because these animals are heavily dependent upon krill, observing predator-prey encounters is vital to understanding how to manage the krill fishery (Miller and Agnew 2000, Link 2010). A precautionary approach to managing the krill fishery and Antarctica's living resources has been proposed to protect one of the world's most abundant species (Boopendranath 2013).

Before the establishment of the 1959 Antarctic Treaty, there was no organization that was responsible for overseeing Antarctica's living resources. Several countries play a part in managing Antarctica and its surrounding ocean (Antarctic and Southern Ocean Coalition 2017). Since the original 12 countries signed the Antarctic Treaty, there are now 28 official parties with the power to vote that meet every year for "Consultative Meetings" (Antarctic and Southern Ocean Coalition 2017). The treaty itself encourages collaborative research efforts between parties and peaceful cooperation to conflict resolution (Antarctic and Southern Ocean Coalition 2017). Collectively, there are now three major agreements under the Antarctic Treaty System: The Agreed Measures for the Conservation of Antarctic Flora and Fauna, The Convention for the Conservation of Antarctic Seals, and the Commission for the Convention of Antarctica's Marine Living Resources (CCAMLR), established in 1982 (Antarctic and Southern Ocean Coalition 2017). Each nation that is a member of the Antarctic Treaty is allowed to be a part of the decision-making process because they are contributing to show their support by, "conducting substantial scientific research activity" in Antarctica. These research efforts are paving the way for marine policy and future conservation efforts in Antarctica.

The Antarctica Marine Living Resources Program of the National Oceanic and Atmospheric Administration (NOAA) is intended to fulfill the United States' (U.S.) mandate under the Conservation of Antarctic Living Resources (CAMLR) Convention. The establishment of the convention was primarily due to growing concerns related to an increase in krill catches in waters surrounding Antarctica. This is why nations around the world are using their research to provide a scientific basis for creating policy that is meant to protect the ecosystem (CCAMLR 2013). Members meet annually to discuss conservation measures related to Antarctica's marine living resources and all that is encompassed within its ecosystem. The Commission manages the krill fishery, including the catch limit, and managers are required to continually work towards ecosystem-based management and conservation by maintaining productivity, health, and resilience under CCAMLR (Watters 2013). The role of the USA in this international agreement requires multiple scientific stakeholders, but the main governmental entity that is performing directed research to support decision making by CCAMLR is located at NOAA's Southwest Fisheries Science Center (SWFSC) in San Diego.

Research by the Antarctic Ecosystem Research Division (AERD) at the SWFSC is focused in several delineated geographic areas known as Small Scale Management Units (SSMUs) where krill fishing has occurred in the past and where predatory birds and mammals forage. The study area for this project is located in SSMU APDPW (Figure 1) and it focuses on the use of animal-borne video loggers that have been attached to chinstrap and gentoo penguins. NOAA has used this new animal-borne video logger technology since 2018, and now has over 50 hours of video of eight penguins foraging from two field seasons.

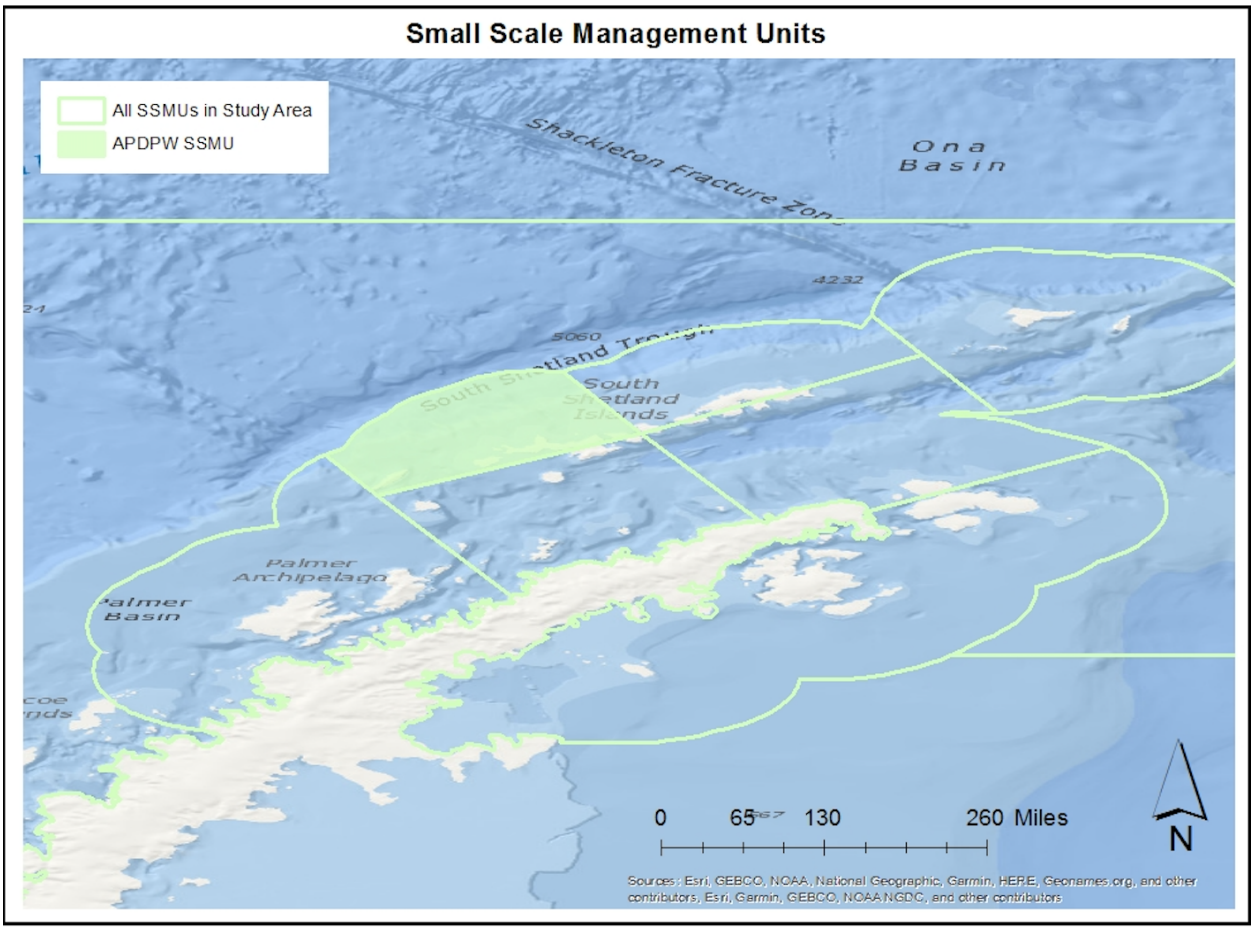


Figure 1. The APDPW SSMU shown in the shaded region of all SSMUs in the study area.

Within SSMU APDPW, GPS tracking data of two chinstrap penguins from the 2018 field season show routes taken to forage (Figure 2). This gives a general idea of distance range in routes these penguins are making in a single foraging trip and five hour video.

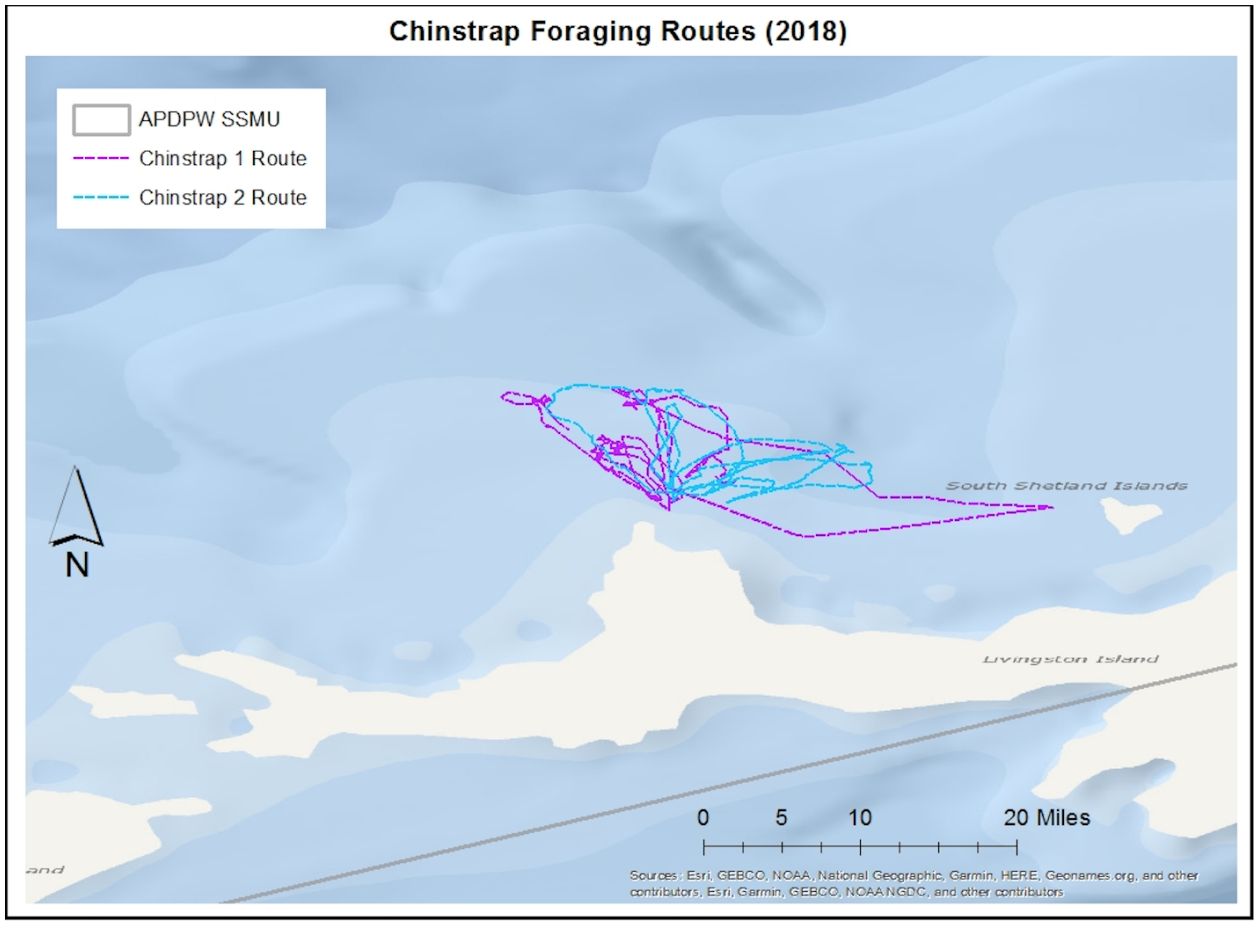


Figure 2. Two individual chinstrap foraging routes from 2018.

Currently, NOAA estimates the size-composition of the krill population using data from penguin diets, but the densities of krill that are encountered by penguins during a given foraging event is not known. Being able to estimate the density of krill from animal-borne cameras would provide unprecedented data on these predator-prey interactions. These videos give a new perspective on krill behaviors, showing exactly how much krill penguins are encountering during their feedings. A better understanding of krill densities from the point of view of a foraging penguin would provide insight to the actual availability of this prey within the penguin's foraging area.

Therefore, in order to efficiently analyze visual data to identify when krill are being encountered, a machine learning, algorithmic process is necessary. A new open-source Video and Image Analytics for a Marine Environment (VIAME) software framework was created for the purpose of automating analysis of underwater imagery collected by NOAA and was released during the summer of 2018. VIAME enables users to analyze mass amounts of visual data, alleviating the burden of manual analysis processing, and provides access to state of the art analysis tools for non-technical analysts. Using this new software has allowed for faster data analysis by filtering through hours of video. This means it is less time spent by analysts manually sifting through data.

The goal of this study was to train a full-frame classifier model using VIAME software framework (Dawkins et al. 2017) to recognize prey and behavioral events present throughout the videos collected by a camera attached to a chinstrap penguin during a foraging event. Through an iterative training process, models were created to process hours of video to find the specific video frames where krill are encountered. Four classes of images scene elements were trained using a RESNET50 model (Kaiming et a. 2015) in VIAME, including two classes of images containing krill. From these images with classes featuring krill, volumetric density of krill was estimated using counts of krill in the frame in relation to imaged volume of the area.

Materials and Methods

Study area and data sources

Ten, thirty-minute long videos from an animal-borne camera that was attached to a chinstrap penguin was used for data analysis. This occurred during the 2018 field season and the penguin foraged on krill in the Southern Ocean at Cape Shirreff, Livingston Island. Data analysis included utilizing the software packages VIAME (Dawkins, et al. 2017) and ImageJ in order to determine krill presence and overall counts.

Creating algorithms in VIAME

The goal of this study was to train VIAME to recognize four different images or conditions present throughout the videos. One chinstrap penguin foraging event, recorded as ten 30-minute video image files were analyzed. The process of using VIAME to classify full-image frames throughout the foraging videos involved multiple steps:

1. Index videos for data storage
2. Train models to create classes
3. Process/run models on videos
4. Export .csv file to use in R

The first step was to index the videos to be analyzed. Each individual frame was extracted from all of the videos at 15 frames per second. Once the approximately 270,000 frames were extracted, the images were indexed using VIAME's indexing process that enables subsequent rapid intake and processing within the VIAME system. Indexing that number of frames took several hours to complete.

Four classes were chosen to represent important conditions encountered by the penguin during foraging excursions. These were "close krill", "all krill" (essentially any krill), "penguin friends", and "penguin surfacing" events. The indexed frames from the newly created database are required for the process of training models to represent the four identified classes. Training was done using VIAME's rapid model generator to detect objects in the frame through an iterative refinement process. The goal is to ultimately be able to use these 4 models on all other visual data collected via the animal-borne video loggers.Model training is based on supplying VIAME's rapid model generator with an example image (or exemplar) for each class. The image examples used for each of the four models and their respective titles can be seen in Figure 3.

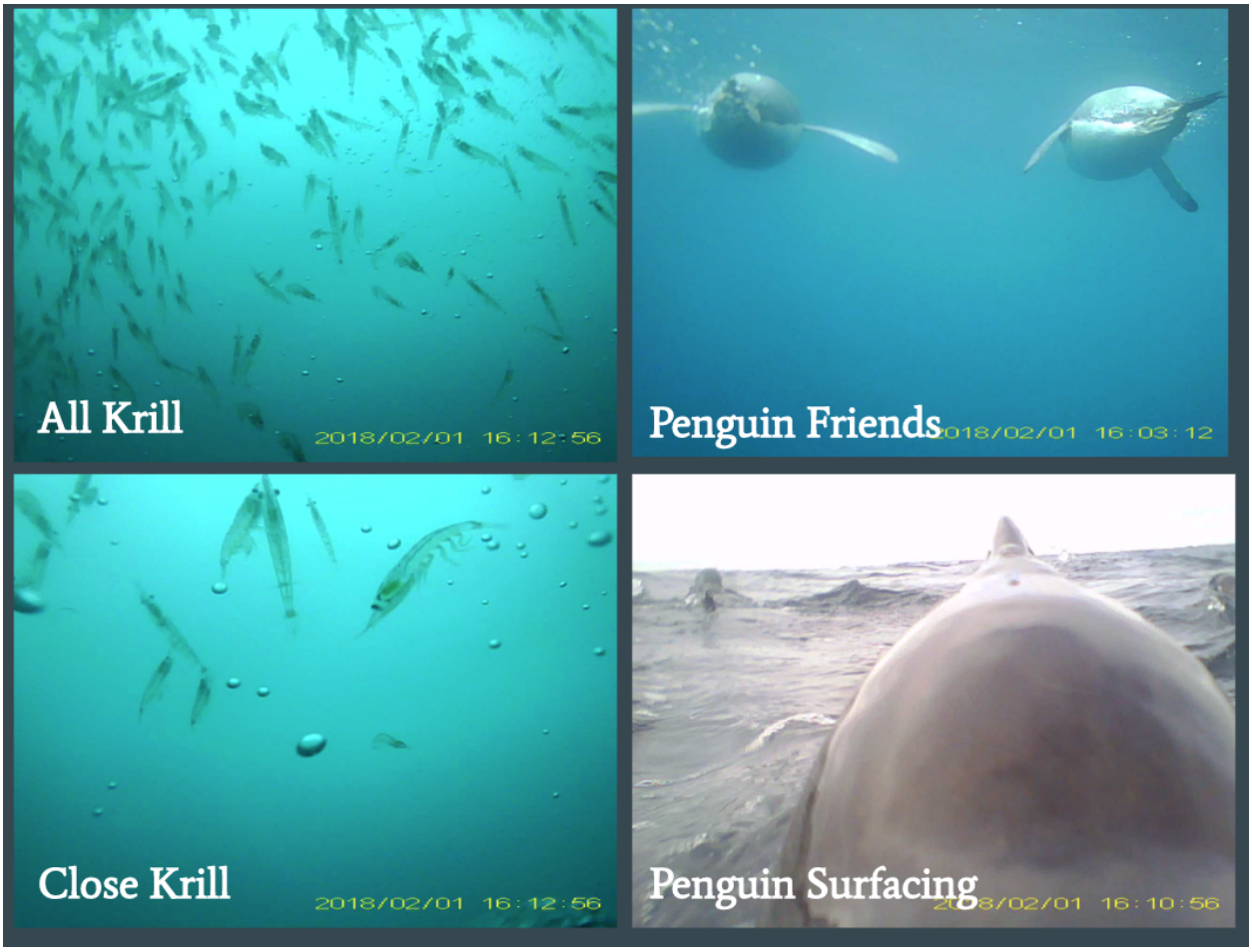


Figure 3. Image examples used to train models.

Each class model was trained separately. The image examples for a class was loaded into VIAME and rapid model training was initiated. VIAME then provides a set of candidat images that are supposed to match the example image class, and the user iteratively indicates whether each candidate frame is positive (belongs to the class) or negative (misclassified). VIAME also provides a set of candidate images for which the model has more uncertainty about to the class in the lower right panel of the GUI (Figure 4). After the user reviews the candidate frames from each set, the refinement process is initiated (menu or button) whereby VIAME adjusts and (theoretically) improves the model based on the corrected set of positive and negative training images. This query and refinement process is repeated through 4-5 iterations until the majority of positive candidate images are acceptable to the user. This helped the model to differentiate between images that might otherwise have been classified inappropriately. Going through several iterations of this process to detect certain images was an attempt to improve the final model and classification of images. When the user accepts the refined model, it must be stored to disk as a support vector machine (SVM) model file in order to apply it to new imagery.

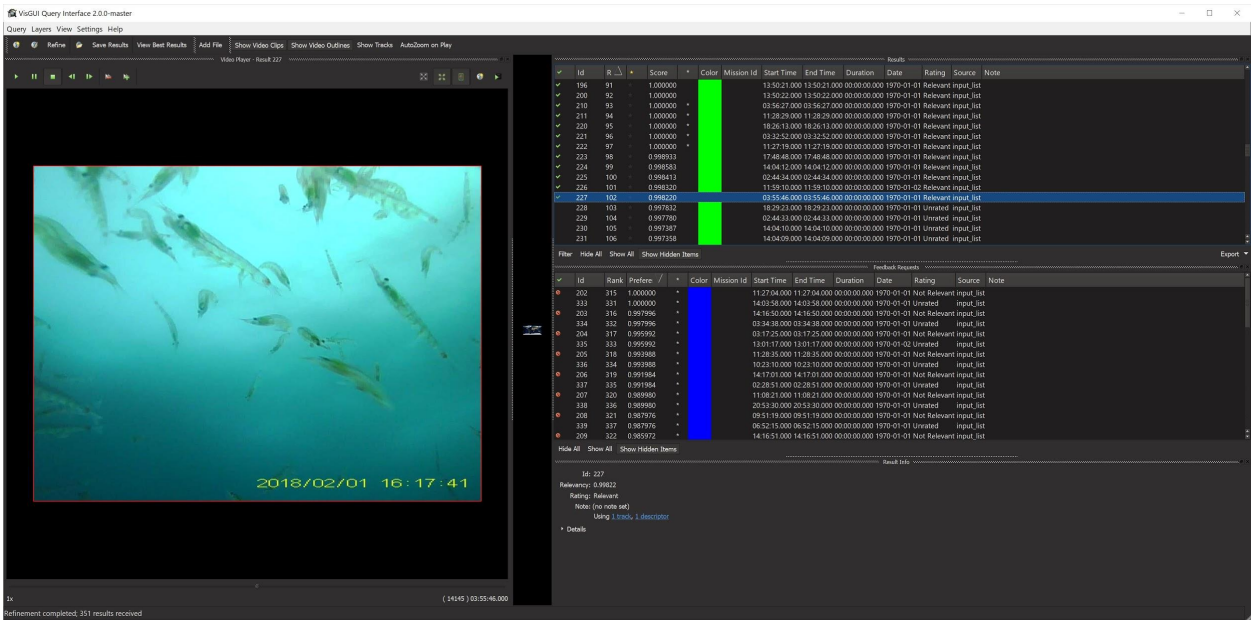


Figure 4. Example graphical user interface of VIAME's rapid model training process, with the current frame under review shown on the left and highlighted (upper right) for Close Krill. Green check marks indicate frames that were reviewed and marked as positives (accurate representations of the class in consideration) and red x marks indicate negatives (candidates that did not match the training class).

After the four models were trained and saved, they were then applied to the collective suite of frames from all of the videos. The process of running these models simultaneously on all of the frames resulted in a spreadsheet that showed which class each frame was assigned to based on the models. Each frame had a confidence level that VIAME computed for each class. Confidence level values represented how well the contents of the frame matched the trained model.

After exporting these results in .csv file format, threshold settings were manually adjusted so that finding the best possible image frames for each class was attainable. This code was then used to export the actual image frames that were classified for each class to visualize the results. Actually being able to see the frames that VIAME was confident in assigning to each class allowed me to determine if the images were being correctly identified. Finally, a final set of frames from each krill class were used to find the estimated density of krill that were being displayed in each image frame.

Calculating Density

Using the threshold level of 0.02 for the Close Krill class and 0.1 for the All Krill class, density was found by taking the number of krill shown in a given frame, divided by the volume of water in meters cubed that is found in the field of view of the camera. The approach to calculating the density was broken down into several steps, but overall there were two key components: (1) counting the most distinguishable krill in a frame and, (2) finding an estimated "standard" volume.

Krill counts were done by utilizing the application ImageJ. Using an automated count system called Find Maxima, a specific number was tested to see which "Noise Tolerance" would produce the most reasonably close results for the estimated count for krill within the frame (Figure 5). Actual krill size to be used in the calculation (in millimeters) was already known due to the studies of gut content of penguins.

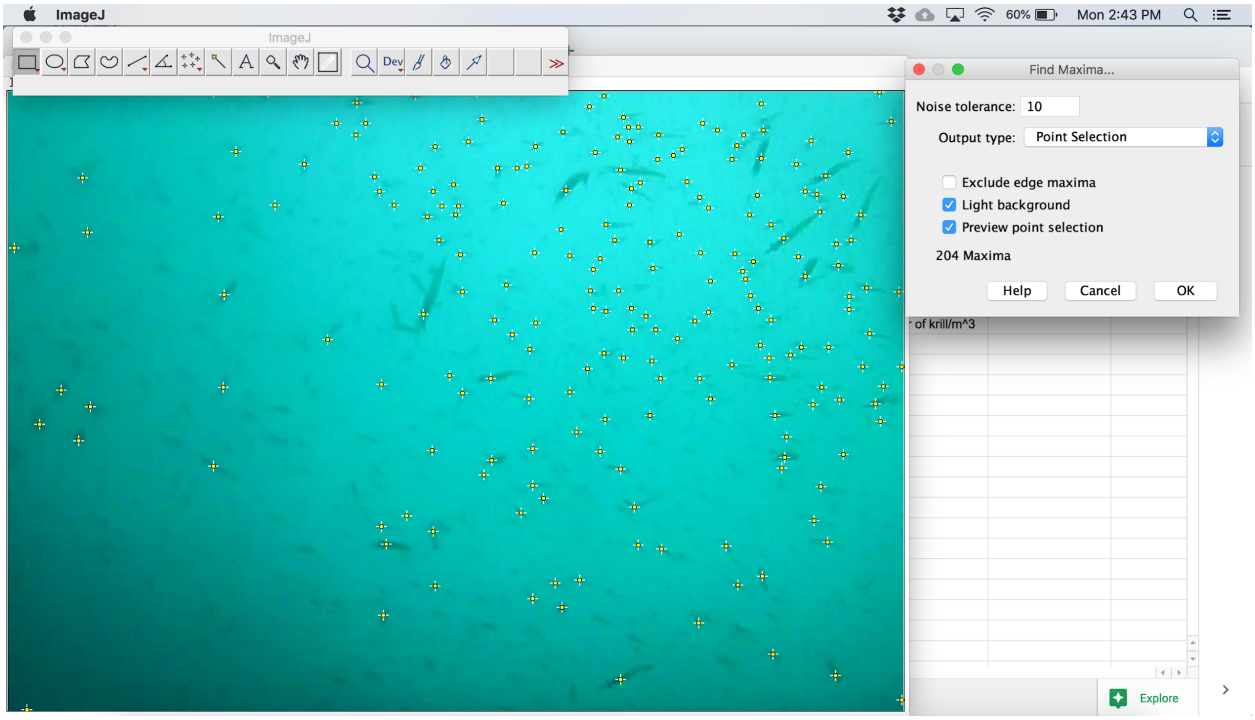


Figure 5. Example of successful ImageJ result for counting krill.

In order to estimate the volume encompassed in the space between the camera lens and the farthest, most distinguishable krill, we assume that the volume can be approximated by a rectangular pyramid. The “unknown” to be estimated is the height, as the frame width and length are fixed. The height was estimated by assuming that the smallest, distinguishable krill in the frame had a mean length of 25 pixels. This mean length of krill was also used in order to convert the length and width of the frame from pixels to millimeters. Because the mean length of krill is known, that could be used to convert the pixel length to millimeters. For instance, the width of the frame was converted to millimeters by taking the known width in pixels (1280 pix) and multiplying that value by the division of length of krill known (43 mm) over the length of krill in pixels (25 pix).

The other known was the camera lens angles. Because the frame width was converted to millimeters and the camera angle was known, the tangent of that could be calculated in order to find the unknown “h” (Figure 6). An important note is that both the width length and camera angle lens had to be divided in half because the height was being taken from the middle of the pyramid. Once “h” was determined, it could be used to find the final the approximate volume of a rectangular pyramid.

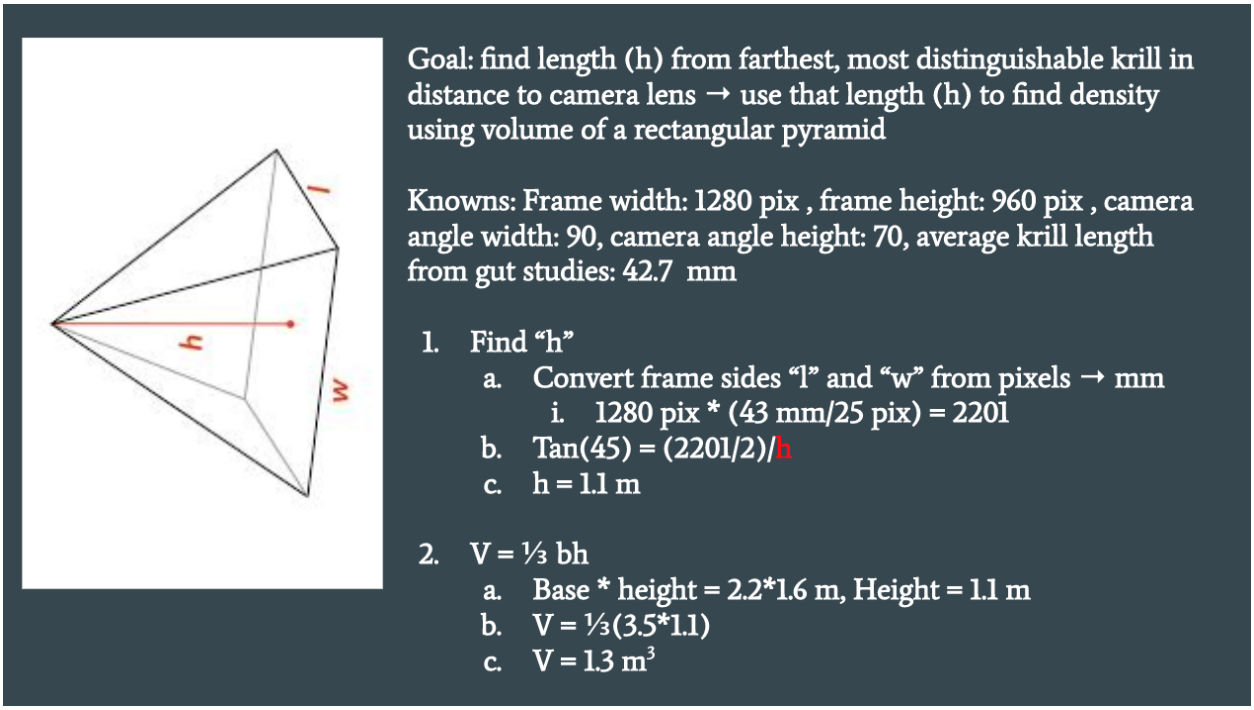


Figure 6. Density calculations with known values.

Density could then be calculated by dividing the known krill counts per frame by the volume in meters cubed. The overall results for average counts and densities for both krill classes can be seen in Table 2 of the Results section.

Results

Four models were trained to recognize four distinct classes during the 5-hour chinstrap penguin foraging event. Out of the 270,000 frames that were classified in each of the four classes the total number of frames for each class came out to 14 for Close Krill, 227 for All Krill, 205,912 for Penguin Friends, and 63,817 for Penguin Surfacing. Collectively, there was a significantly higher amount of frames VIAME was confident in detecting relating to the penguin classes as opposed to the krill classes. Out of the total frame set, the Close Krill final class made up .005% and the All Krill class came out to .08%. The Penguin Friends class came out to 76% and the Penguin Surfacing was 24% of the total frames.

In order to visualize where VIAME was detecting frames throughout the video and their corresponding confidence level per class, the results were input into a code. This code was created to plot a short time series of each instance there was a detection per class and its exact level of confidence for that detection. In Figure 7 below, the x-axis is the number of frames as the videos progress from frame 1 to 270,000 and the y-axis is the probability, or confidence level that VIAME was detecting the correct images that were previously trained in each of the models. Though there are much lower detections for the krill classes, the confidence levels are relatively high and there do not appear to be many results under the 0.5 threshold level.

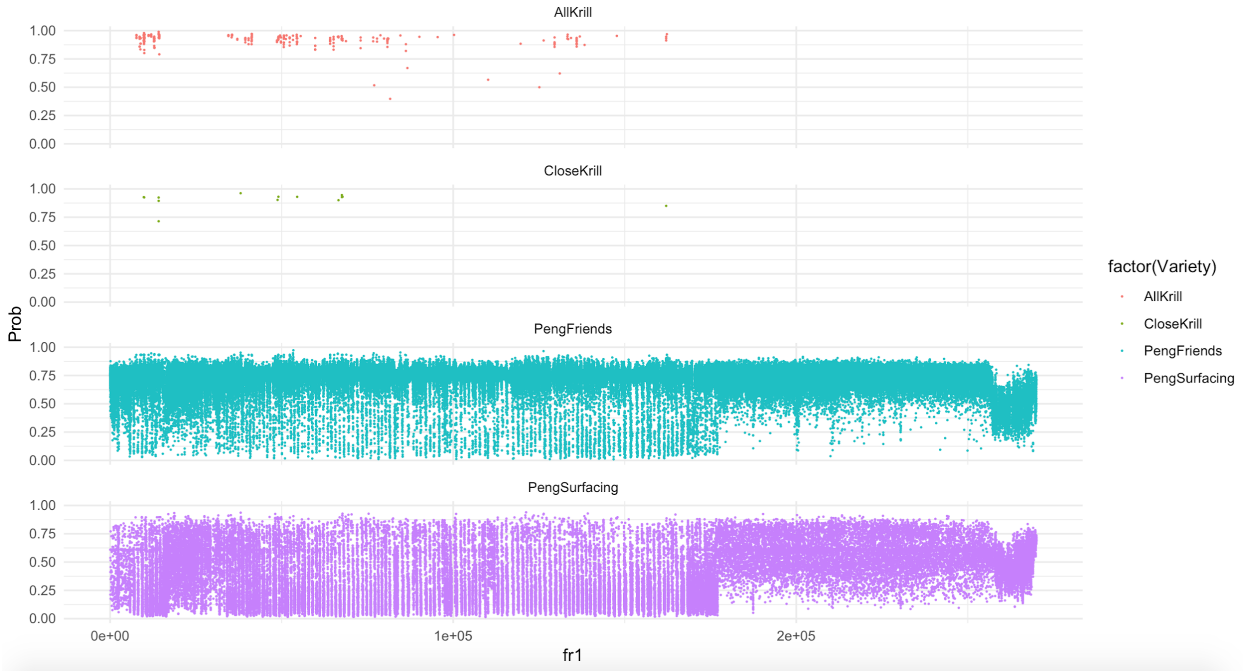
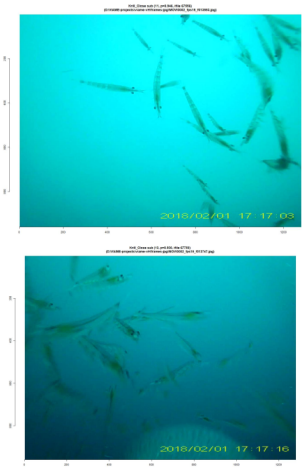
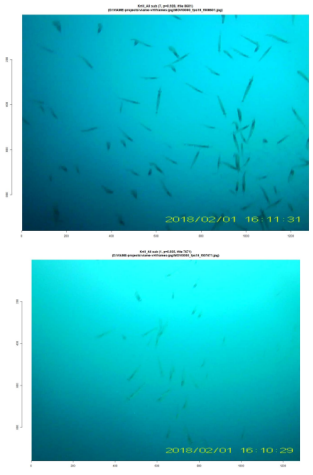


Figure 7. Frames detected and confidence level for each class..

Further analysis led to using another code to provide the actual images from detected frames for each of the krill classes. The All Krill class had 263 total frames that were detected and the Close Krill had 14, so a count was done to see how many frames were correctly and incorrectly classified for each of the classes. Some incorrect examples could include images like the bubbles that were detected instead of krill as seen in Figure 8 below.

Conf thresh	**Close Krill (14 Frames)**	**All Krill (263 Frames)**
[>0 Close Krill] [>0.1 All Krill] (confidence threshold that leads to all images being correctly classified)		
0.0 (unrestricted) (Incorrectly classified frames)	N/A - All 14 Frames were correctly classified	

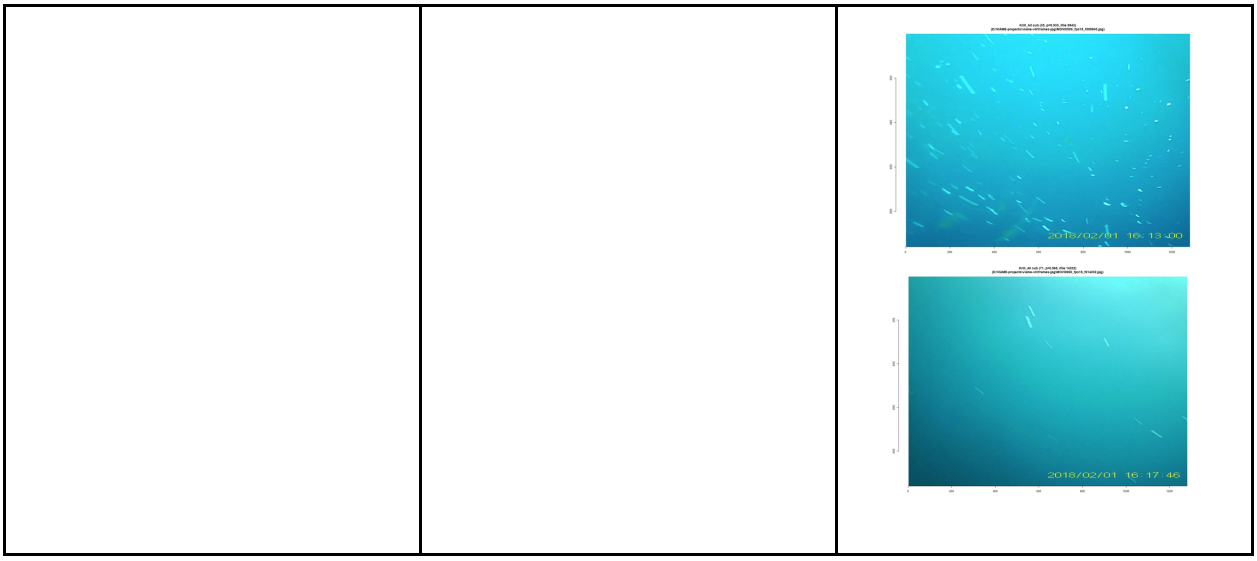


Figure 8. Examples of images that were correctly and incorrectly classified for each krill class under different threshold levels.

Closer examination was needed in order to evaluate the performance of the models and classifying process. For the Close Krill class, all 14 frames that the software was confident in were correctly identified. For the All Krill class, out of the 263 images that VIAME detected, there were 7 images that were incorrectly identified. The Close Krill class had a low threshold in order to produce the most results possible and the All Krill class had a higher threshold of 0.1 (Table 1). The greatest misinterpretation appeared to be because of bubbles that took up the frame and were similar in size to krill that the penguin was encountering.

Table 1. Number of correctly identified frames out of the total frames per class.

	Close Krill (> 0.02 Threshold)	**All Krill (> 0.1 Threshold)**
Accurately Classified Frames (True/Total-per-predicted-class)	14/14 (100 %)	220/227 (97%)

Once the detected frames were identified, density could be estimated. The mean density estimated from the All Krill class was 44.1 m^{-3}, approximately double the mean density of krill in the Close Krill images 20.0 m^{-3} (Table 2).

Table 2. Krill densities (mean m^{-3} (standard deviation)) estimated from images collected by a penguin-borne camera.

	Close Krill (14 Frames)	**All Krill (263 Frames)**
Average Krill Count (Individuals)	27 (31)	55 (50)
Average Density (m^3)	20.0 (23.4)	44.1 (37.3)

Discussion

The goals of this study were to train models to automatically classify images with krill for tens of hours of videos, and to provide the first estimates of krill densities obtained from animal-borne cameras. Classifier models results were 100% correct for Close Krill and 97% correct for the All Krill classes. Threshold confidence values were set at 0.0 for Close Krill and 0.1 for All Krill. No assessment was done to determine whether any of the images classified as Penguin Friends & Penguin Surfacing contained krill images.

The adequacy of this process was determined after being able to run the trained models on frames and observing the final classified image results. There was a much higher percentage of frames that resulted from the penguin classes than the krill classes. This is likely due to Penguin Friends also serving as an “Open Water” class because the open water images most closely corresponded to the underwater images with the penguins swimming. One study found that chinstrap and gentoo penguins spend approximately 76% of their forage time underwater, and the other 24% was spent on the surface (Wayne et al. 1986). With the caveat that the classifier model might have misidentified frames (e.g. Penguin Friends instead of krill), this study suggests that chinstrap penguins encounter krill during about 0.1% of the time while underwater. If the trained model did incorrectly classify certain instances where krill was encountered but not identified, it is not expected to be much more than the krill encounter results that were accurately classified. For the combined krill classes, the volumetric density for the Close Krill class ranged from 3 to 84 m^{-3} and the All Krill class ranged from 4 to 122m^{-3}. While these ranges are not significantly different, the All Krill class did have the higher maximum value, reinforcing the trained models were effective in detecting the closer, large krill meant for the Close Krill classifier as opposed to smaller, more abundant swarms that would be classified in the All Krill model.

Additionally, from each of the ten, 30-minute videos, the detected frames had the specific frame number and corresponding video that it came from. This made it easier to reference where in time krill were being encountered by the penguin. However, after video 6, there were no more detected frames that VIAME was able to find. This is could be a classification error, or it could also be that at the end of the foraging trip, the penguin was not encountering any prey.

One of the largest concerns was that other images that should have had a model trained for their own class were being classified into the next closest image that VIAME thought was suitable. This could include images such as open water, bubbles, or full bodied penguins above water that were commonly observed when training the final models for this study. Training models to detect other images such as these may have provided more distribution of results between classes. There were also issues when it came to the software crashing due to memory necessities and before running the models collectively on all of the frames, the software was unable to run models on all of the movies at once. The VIAME software has other options available for training models, so using one such as Deep Model Generation may have been more effective than the Rapid Model Generation that was used.

It will be beneficial to have VIAME correctly index imagery from videos to frame number and time, so that the user does not need to export video frames to images, as this process is time consuming and requires extra storage space. The developers have been notified and are working on this bug fix for

the next release. When this is done, the iterative training process can be performed on the videos themselves instead of on extracted frames from the videos. Although there some bugs were encountered, the software developers were responsive to bug reports and fixed bugs with patches or new releases as problems were reported. The rapid model generation process was user-friendly and effectively classified imagery.

Density calculations

Potential sources of error could have occurred when calculating the density. The ImageJ automated krill count method was used for simplicity and because of time constraints with this project. A visual count may have been more accurate, but human biases may have produced less accurate counts, and would not have been reproducible across users (REF). More complicated methods are available for detecting target blobs in images, but none are guaranteed to provide higher accuracy or be worth the time to try to implement. A neural network based, deep-learning detector could be trained to provide potentially more accurate automated detection counts of krill, but these requires thousands of manually annotations and would need to be trained for many different target visual appearances. For example, a detector trained for close krill would not be applicable to the distant, faint krill targets or krill targets in regions of the image affected by motion blur. Noise Tolerance level was adjusted for each frame in order to get results that better matched the count of krill than would have resulted from manual counts. The automated krill detection process might not have always been reliable because it detected most bubbles, each eye of a single krill, and sometimes indistinguishable items in the distance that might not have been krill. Sometimes there were numerous targets in the frame that were too blurry to confidently identify as krill. Miscounting targets could play a part in underestimating the value for density because there are more figures that are krill than are being counted. The three tier method for determining distinguishability of targets can be seen in Figure 9.

After krill counts were estimated, finding volume was the other component to finding density results. A minimally resolvable krill target (r* in Figure 9) represents a krill located at the maximum resolvable range of the camera, beyond which targets have insufficient detail to be reliably identified as krill. Lengths, in image pixels, of a sample (N= ##) of minimally resolvable krill targets were measured from the images, resulting in $\underline{L}_{r*} = 25$ pixels. The mean imaged length of these krill targets is assumed to represent krill actual lengths measured from penguins diets collected just after a foraging excursion, where $\underline{L}_{krill_diet} = 43$mm. This image-to-world conversion factor ($\underline{L}_{krill_diet}/\underline{L}_{r*}$) is then used to solve for resolvable range in world coordinates (mm). This includes using a geometric relationship that includes the known lens field-of-view angle in horizontal direction (45°), and image width W_{world} = 2202 mm. Imaged volume is then obtained by assuming a pyramidal imaged volume, where $\underline{V}_{imaged} = W_{world} * L_{world} * H \ / \ 3$= 1.33 m^3 and H = maximum resolvable range.

Figure 9. Examples of resolvable (r), minimally resolvable (r*), and unresolvable (u) targets in an image from the penguin-borne camera.

Krill density and penguin foraging behaviors

Although VIAME was accurate in the confident detections it produced, the significantly low percentage of final detections for the krill classes could also pose a problem in determining average density. Without the correct number of total frames of krill encounters, the averages for densities could be altered if there were a higher or lower number of counts of krill in more detected frames. Additionally, krill are an animal that shrink and change in shape (Sun 1995), so there may be some images of krill that are not being accounted for by using the automated ImageJ system.

A notable result that came from utilizing VIAME is the lower density from the Close Krill class as opposed to the higher number of density for the All Krill class. This could largely be in part due to the fact that as the penguin was approaching the krill to feed, the krill would scatter and there would be less krill for the penguin to forage on. Therefore as the penguin got closer, there were less krill in the field of view for the Close Krill classified images. Throughout the ten videos, the penguin seemed to be exhibiting a pattern of diving around a krill swarm and attacking from below. This could be an adapted response to krill behavior. Krill have shown trends in their behavior such as utilizing a diel vertical migration through the water column (Croxall et al. 1985, Godlewska & Klusek 1987, Hampton 1985, Kalinowski & Witek 1980, Loeb & Shulenburger 1987). In concurrence, they might also use that diel pattern to densely swarm together during the day and scatter at night (Everson 1982). Chinstrap penguins have shown a pattern in diving the most during the day, which could be due to utilizing light for the best visual purposes or making the most of the diurnal patterns for both higher densities and

known behavior of krill (Bengston 1993). However another study done by Aileen Miller and Wayne Trivelpiece showed that chinstrap penguins dove at the same depths at night when ambient light was most restricted, which brought them to believe that diving patterns corresponded more with krill diel vertical migration (Miller 2008). Overall, chinstrap penguins showed diving patterns that coincided with krill diel vertical migration and this could be the driving factor behind their position of attack. A lower density upon closer attack would make sense because there are less krill in the frame, and the ones that are there are closer to the camera, providing a lower count of total krill to be input into the density equation.

When reflecting on the observed behavior throughout the five hours of foraging time, the krill did not seem to have a distinct pattern or distribution as the penguin approached swarms. If there was more time with for this study, it would be helpful in knowing how long it took the penguin to reach higher densities of krill as it continued to make its way farther away from land into the ocean. This gives a spatial perspective of where the highest krill populations occurred and NOAA could then focus on acquiring data in these high density areas to see how they change over time. It could lead to a greater understanding of how the penguins would be affected if those krill populations were to significantly shift due to external factors such as the krill fishery and climate change.

Future possibilities

Since the 1960's, animal-borne logger technology has greatly advanced and allowed scientists to gain knowledge on animals that live in otherwise limited settings. Even though advancements of these technologies has provided higher resolution data, there is oftentimes a lack when it comes to visualizing actual prey availability (Wilmers 2015). If the cameras could be used to detect high density krill swarms in real-time, that data could be logged and tracked over time, ultimately being used for spatial modeling purposes or influencing future marine policy. The cameras could potentially be fitted to have specific models embedded in their software so that classes such as "All Krill" could be detected as they were being approached. In comparison to studying gut contents and finding sizes of krill, understanding how densities of krill are changing over time and observing where they are occurring spatially gives an entirely new perspective. Tracking this close-range interaction between predators and prey over time could be a key aspect in influencing policymakers on strengthening the protection of krill in the Southern Ocean.

With advancements in technology, the possibility for resolution quality to improve or longer batteries/memory would allow for an even more comprehensive look at first-hand penguin foraging behavior. Being able to continue to develop and execute these studies with animal-borne loggers could ultimately contribute to influencing more efficient ways to implement the glider studies as well, in terms of having a better understanding of where to deploy the gliders in areas that are known to have higher krill densities. Additionally, these animal-borne cameras and autonomous gliders would take the place of the much more costly ship-based studies. Using these instruments would be beneficial in terms of cost, safety, and accessibility. By making refinements to the VIAME process and figuring out what methods work best with the visual data that NOAA is acquiring, the trained models could be an efficient filtering tool. The software has shown to be effective, so now it is just a matter of finding the most efficient way to classify models within VIAME to produce the most accurate and highest level of results.

Conclusion

The VIAME software has shown that it is an effective tool for filtering through visual data. For the first time, the use of video loggers on penguins has been used to estimate densities of krill encountered in a single foraging trip. Using this first-hand data provides a better understanding of spatial connections between predators and prey that could contribute to influencing marine policy or krill fishery management. As NOAA continues to develop technologies such as this, they will continue to fulfill their mandate under CCAMLR by providing the highest level of ecosystem-based research, assisting in maintaining a sustainable and resilient ecosystem in the Southern Ocean.

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