Classifying Hawaiian Monk Seal Foraging Behaviors Using Metrics Based on Triaxial Accelerometry: Pilot Data, Evaluation, and Future Research Recommendations

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Executive Summary

Animal-borne instruments are an important tool in studying the underwater behavior and ecology of marine mammals, including the endangered Hawaiian monk seal (*Neomonachus schauinslandi*). As technology has improved, instruments have become smaller enabling less impactful data collection from smaller/younger animals. Multiple sensors have become miniaturized, allowing a single instrument to collect numerous metrics to help assess animal movement and infer behavior. Additionally, analytical algorithms have become more computationally efficient, offering the promise of onboard calculation so that high-resolution data can be summarized and effectively transmitted over satellite uplinks, avoiding the need for repeat animal handling for retrieval of archival instruments. All of these advancements stand to improve the safety and data quality of foraging research conducted on Hawaiian monk seals.

In order to take advantage of emerging technology to minimize animal impact, and cost, and to streamline future analysis of Hawaiian monk seal foraging behavior and ecology, we first needed to evaluate the utility of accelerometry-based metrics for classifying monk seal behaviors, based on comparison to behaviors observed in seal-cam video footage.

In this report, we addressed four major objectives:

1) Classify monk seal behavioral data from video footage for comparison with accelerometry patterns;
2) Use accelerometry metrics to distinguish activities to refine activity budgets by depth;
3) Calculate pitch to evaluate its success for distinguishing foraging events / prey capture;
4) Test algorithms (available in commercial tags) to evaluate their success for distinguishing foraging events/prey capture in this species.

Key findings under each objective were as follows:

1) There was high individual variation in ethograms, but we noted a trend for juveniles to use more energy-intensive foraging strategies.
2) Sleep was easily distinguished from other behaviors (up to 89% accuracy based on standard deviation of depth and accelerometer X-axis). Sleep typically occurred within the individual seal's depth zone of primary use, whether that was deep or shallow.
3) The pitch metric calculated from the accelerometer was highly variable and not as steep as found in one previous Hawaiian monk seal study. We found that pitch was unlikely to provide a clear indicator of monk seal foraging activity.
4) The algorithm showed promising correlation between activity count and prey-capture activity (r=0.88 within bottom segments of dives). This algorithm may provide a good index of foraging activity, but is unlikely to provide precise quantification.

Recommended future research actions include:

- Continue to expand sample sizes to improve power for inference, particularly relative to juvenile samples, for comparison between main and Northwestern Hawaiian Islands within the same timeframe.

- Cross validate analysis from previous data sets aiding comparisons among data sets, contributing to greater sample power for analysis, potentially engaging citizen scientists.
- Maximize use of existing data sets (e.g., Digitize old CritterCam footage so that data can be more easily archived and revisited).
- Test additional algorithms emerging / available from other companies (SMRU, CATS).
- Expand on initial outcomes from this study to consider developing Hawaiian monk seal-specific algorithms for distinguishing key behaviors of interest, likely benefitting from partnerships with computer scientists.

BACKGROUND

Animal-borne biologging instruments are a crucial tool in studying the underwater behavior and ecology of marine animals, including the endangered Hawaiian monk seal (*Neomonachus schauinslandi*). The Hawaiian Monk Seal Research Program (HMSRP) has a long history of using technology to study the movement, behavior, and foraging ecology of Hawaiian monk seals (Abernathy 1999; Cahoon 2011; Parrish and Abernathy 2006; Parrish and Littnan 2007; Stewart et al. 2006). While several instruments provide dive summaries to identify the depth-based habitat used by seals, seal-mounted cameras (seal-cams) have been essential in revealing the ways that monk seals interact with their foraging habitat. Seals may swim in the upper water column (typically making shallow dives of 15–20 m) while transiting to an offshore bank, but most of their swimming time is focused near the seafloor where they are able to find demersal and benthic prey (Parrish et al. 2000). The Hawaiian monk seals' foraging strategy of focusing on cryptic prey leads to generally continuous foraging as seals move between small patches of habitat harboring individual prey (Wilson et al. 2017a). Seals show the greatest foraging effort in benthic areas with moderate complexity, such as sand beds with occasional rocks or coral heads (Parrish et al. 2000; Wilson et al. 2017a). While at sea, monk seals have also been recorded sleeping (34% of time) and socializing with other seals (9% of time; Parrish et al. 2000).

When monk seals find a prey item, they typically invert their body, using their head to dig down into the sand, or turn over rock or coral fragments to catch hiding prey (Parrish et al. 2000; Wilson et al. 2017a). This characteristic and abrupt change in body position has made it possible to develop models that can successfully use sensors, such as triaxial accelerometers, to detect prey capture attempts from biologging instruments (Wilson et al. 2017a). These models have helped to show that the probability of prey capture attempts increases on long, deep dives with more time at the bottom and with increased body motion (Wilson et al. 2017a).

Monk seals appear to develop individualized foraging strategies. While inter-individual variation is high for space use and dive patterns, intra-individual variation is much lower, indicating varied individual specialization rather than random opportunism (Abernathy 1999). Seals used different feeding tactics in different habitats; some searching sand fields capturing hiding prey by burrowing into the sand, others searching large loose rocks to find prey underneath (Parrish and Littnan 2007). Beyond individual specialization, it is worth considering whether regional ecology or animal development shape these foraging strategies. Seals in the Northwestern Hawaiian Islands (NWHI) tend to spend less time hauled out (31%; Harting et al. 2017) compared to seals in the main Hawaiian Islands (MHI; >40%; Cahoon 2011; Wilson et al. 2017b). Given that body condition and survival rates tend to be higher in the MHI (Baker et al. 2011), this may be an indication that MHI animals are able to satisfy their foraging needs with less time at sea (Wilson et al. 2017b). In addition to geographic variation in foraging, there is evidence that juvenile seals adjust their foraging habits over time, either as they develop physical strength or increase local knowledge (Norris et al. 2017; Parrish et al. 2005). Understanding juvenile foraging behavior and the development of mature foraging strategies is particularly important in revealing the mechanisms underlying poor juvenile body condition and an important survival bottleneck limiting recovery of the species (Antonelis et al. 2006; Baker and Thompson 2007).

As biologging technology has improved, we have new opportunities to delve deeper into these ecological differences that may influence the foraging ecology and survival of monk seals. Instruments have become smaller enabling safe data collection from smaller animals, allowing us to better study the juvenile age class. Multiple sensors have become miniaturized, allowing single instruments to collect numerous metrics to help assess animal movement and infer behavior. Additionally, analytical algorithms are becoming more computationally efficient, offering the promise of onboard calculation so that high-resolution data can be summarized and effectively transmitted by satellite uplink. To take advantage of emerging technology to streamline future analysis of Hawaiian monk seal foraging behavior and ecology, we first needed to evaluate the utility of sensor-based (primarily accelerometry) metrics for classifying monk seal behaviors, based on comparison to behaviors observed in seal-cam video footage.

OBJECTIVES

With an overall goal of streamlining future analysis of Hawaiian monk seal foraging behavior and ecology, we addressed four major objectives.

1) Classify monk seal behavior from video for comparison with accelerometry signatures.
2) Use accelerometry metrics to distinguish activities to refine activity budget by depth.
3) Calculate pitch (previously published metric) to evaluate success for distinguishing foraging events/prey capture.
4) Test algorithms (available in commercial tags) to evaluate success for distinguishing foraging events/prey capture.

METHODS

Instrument deployment & seal-cam data set

We targeted a stratified sampling of seals that would allow comparisons between geographic regions and age classes that could play a part in shaping foraging behaviors. We sampled seals at French Frigate Shoals representing one of the largest, but most volatile, populations in the NWHI, and Molokai representing one of the key population centers in the MHI (Figure 1). While this sampling effort is ongoing to obtain robust samples for comparative analysis, this report focuses on preliminary data from seven animals instrumented in 2018–2019 to refine analytical approaches (Table 1).

After a thorough on-site risk assessment, target seals were captured with a hoop net and manual restraint. Seal weights were visually estimated and seals were sedated (diazepam 0.1–0.25 mg/kg, IV), providing approximately 45 min of sedation for procedures which included sample collection for health monitoring as well as instrumentation. Instruments were attached on the seal's back between the shoulder blades, using a thin layer of 10-min epoxy (Devcon, product number 14251) to the outer pelage. In addition to the multi-sensor seal-cam (monk seal model Customized Animal Tracking Solutions; CATS), each seal also received an Argos satellite tag (Wildlife Computers Spot6 or Splash10), and a VHF transmitter (ATS MM120) was attached to the seal-cam to aid in tracking and relocating seals for camera retrieval. We began searching for instrumented seals as soon as 2 days after instrument deployment. When the seal was relocated in a safe area for capture, it was captured either with a hoop net or stretcher net (in the case of smaller juveniles), and physically restrained while one team member cut the camera free from its mounting platform (typically <1-min restraint time). The mounting platform and satellite tag were left in place. All activities were conducted under NMFS Permit 16632-02.

These animals constitute the study population for this pilot analysis combining video and sensor data to describe monk seal foraging behavior.

Table 1. Seals instrumented with seal-cams in 2018–2019 in both NWHI and MHI.

Seal	Site	Sex	Age Class	Deployment Date	Sensor Data (h)	Video Data (h)	Data Quality Notes
Y2JU	FFS, NWHI	M	J2	4/18/18	72	8.5	Good
YR29	FFS, NWHI	M	A	4/19/18	96	6.0	Good
Y76F	FFS, NWHI	M	S3/4	8/31/18	96	9.0	GPS failed
Y3RD	FFS, NWHI	M	J2	6/7/19	0	0	Not retrieved
R7AW	Molokai, MHI	M	S4	6/11/18	96	6.0	Depth failed
RJ08	Molokai, MHI	M	J1	6/11/18	96	6.5	Good
RJ40	Molokai, HMI	F	J2	2/4/19	72	7.0	Good
RKB0	Molokai, MHI	F	J2	2/5/19	48	6.5	Good

NWHI = Northwestern Hawaiian Islands; FFS = French Frigate Shoals; MHI = main Hawaiian Islands

Objective 1) Classify monk seal behavior from video

Trained volunteers viewed the seal-cam footage to record seal behaviors. We recorded behaviors in the program Behavior Observation Research Interactive Software (BORIS), which provides a viewing screen and coding options to easily record an ethogram (a log of all the different kinds of behavior or activity observed in an animal) associated with video timestamps while viewing the video. We recoded general habitat types and behaviors describing transit, foraging, interacting, and resting (Table 2). Full ethograms were plotted showing all observed behaviors along with the habitat. Additionally, key behaviors of interest were plotted in relation to depth as well as accelerometer data (example in Figure 2). All plots were made using R packages including ggplot.[1]

While previous technology required merging of independent data streams in post-processing (as in Wilson et al. 2017a), the CATS multi-sensor seal-cam platform offers the substantial benefit that all sensors and video are controlled by a single circuit board, and thus have matching timestamps. Sensors included in the CATS seal-cam model included the following: pressure (depth), temperature, light (primarily for triggering camera lights), GPS, and triaxial (i.e., measuring on X, Y, and Z axes) accelerometer, magnetometer, and gyroscope. The video recording function was set to be enabled after a seal dove deeper than 2 m (in an attempt to avoid using video time while hauled out), video would record for a 30-min segment, after which it would be disabled for 3 h. All other sensors recorded continuously throughout deployment. Data sets for video, GPS, and other sensors required separate post-processing, and outputs had to be combined after the fact. Triaxial data were collected at the greatest frequency (20 or 50 Hz): however, to conserve battery power, other sensors such as pressure (depth) and GPS (location) were only collected at 1 Hz, likewise video scoring was recorded at 1Hz. The values for 1 Hz data were applied to all higher-resolution data points within the appropriate 1-s interval. The data sets were combined using basic commands in R.

Objective 2) Use accelerometry metrics to distinguish activities

Most studies of monk seals in the NWHI have relied on instruments that send data by Argos satellite. To maximize information sent in these satellite transmissions, depth data (when recorded) are typically binned over 6-h periods. This provides a good general idea of the types of habitats utilized by an instrumented animal, but offers little insight into the behaviors occurring at each depth. For instance, most such dive summary data suggests that Hawaiian monk seals spend more than 80% of their time at depths less than 40 m (Abernathy 1999; Stewart et al. 2006). Yet some prey species that have appeared to be important in diet analysis (based on fatty acid analysis; Iverson et al. 2011) inhabit much deeper waters, raising the question of whether shallower water might host a range of activities such as transiting and sleeping, whereas deeper dives might be more dedicated to prey capture. By using data from seals with cameras and accelerometers, we can develop and verify methods of characterizing the activity budgets (a summary of an animal's activities over time) of seals using different depth zones, and ultimately, better able interpret dive patterns summarized by instruments reporting coarser dive data.

We constructed a number of plots to visually explore the complex multi-sensor data. We first created simple two-dimensional plots, showing the seal's depth and accelerometer readings in

[1] https://github.com/tidyverse/ggplot2

relationship to behaviors classified in the video. Next, we used depth, accelerometer, and magnetometer readings to reconstruct the seal's tracks in its underwater activities using the TrackReconstruction R package (Battaile and Battaile 2019). These plots helped to understand the ways in which these sensor data can be used to infer activity of the seal.

One of the most visually striking patterns in the data was the stability of both accelerometer and depth readings when animals were sleeping underwater. Thus, we set out to develop an activity metric to distinguish between active and resting bottom time. Accelerometer and pressure (depth) data was used to investigate and quantify sleep, foraging and other behaviors. Behavioral classification from video analysis was used to validate the ability (or inability) for accelerometry signals to differentiate between behaviors.

Seal Y2JU was found to have spent considerable time sleeping while the seal-cam video was engaged, so we used this individual to define the accelerometer and depth signals associated with sleeping. We used the running standard deviation (SD) over a 5-s period to identify static periods associated with sleep; SD < $0.08\ m/s^2$ on the sway (Y) axis and SD < 0.5 m in depth. We also used various levels of depth to stratify further our results. The depth standard deviation tended to eliminate times during descent and ascent when animals conserved energy by gliding during times of negative or positive buoyancy. The use of depth eliminated times when the animals were on land, and times when the animals were gliding during transit at deeper depths (>15 m).

In the development stage, we worked with the subset of data for which we had both video and sensor data, so that behavior classifications from the video could be used to validate the metric. Once the metric was providing reliable results in agreement with the video-based classification, we applied the metric to the entirety of the sensor data to classify active and resting periods throughout each seal's full deployment period. These metrics were constructed, validated, and applied using R packages including rbl[2].

Objective 3) Calculate pitch for distinguishing foraging events / prey capture

Prey capture (or behavior associated with attempts to catch prey) is a behavior of primary interest. In detecting and quantifying prey capture behavior, we can better understand monk seal habitat use, energetics, and ecological differences among age classes or geographic regions. Previous research using seal-born video has shown that body inversion can be a tell-tale sign of prey capture effort (Parrish et al. 2000), and accelerometer data has shown promising potential to identify prey capture attempts using pitch-based metrics (Wilson et al. 2017a). Accelerometers have been successful in determining activity budgets in some pinnipeds and providing important conservation information, particularly for vulnerable life stages. Using only accelerometry data that had accompanying video data, we calculated basic triaxial accelerometer statistics associated with each behavioral classification (statistics included mean and standard deviation of each accelerometer axis, as well as the mean pitch and roll angle and standard deviation). The means of pitch and role were calculated using functions in the TagTools package in R[3]. The accelerometry data was first standardized to gravitational units using the maximum and

[2] https://rdrr.io/github/SESman/rbl/
[3] https://github.com/stacyderuiter/TagTools

minimum values of static acceleration specific to each tag and assuming a linear model for the accelerometers using the TrackReconstruction R package (Battaile and Battaile 2019).

Objective 4) Test algorithms for distinguishing foraging events / prey capture

While high-frequency accelerometers provide fine resolution data to describe animal behavior, the utility of such instruments can be limited by the necessity to retrieve archival instruments (the only option capable of holding such large data files). This can be especially limiting when studying Hawaiian monk seals, where there are multiple seal- and environmentally-derived variables that can constrain the range of suitable conditions for elective capture, handling, and disturbance. Thus, as technology develops, it will be useful to adapt classification algorithms such that they can be computed onboard instruments to transmit brief summaries, rather than archiving high-frequency data in its entirety. Algorithm development and validation are important steps in this process. Here we employed the "Dive Segment Analysis" (DSA) algorithm, developed by Wildlife Computers, and assessed its performance based on comparisons to our video classification.

The Wildlife Computers DSA algorithm was originally developed for a different species (elephant seals, *Mirounga angustirostris*), with foraging strategies that are very different from Hawaiian monk seals. Thus, while using an existing algorithm may be the most expedient, testing was important to ensure that the algorithm captured meaningful patterns in monk seal foraging activity. However, the algorithm is based on relatively basic features of dynamic movement, so there is reasonable hope that the method may be transferable.

The first step in the DSA algorithm is identifying a dive; requiring the depth sensor to register deeper than 3 m. The dive is then segmented using a broken stick algorithm (Cox et al. 2018). In short, this algorithm seeks the most extreme inflection points in a time-depth data series and uses these inflection points as boundaries to split the dive into five segments. The segmentation is particularly useful because different levels of dynamic body activity might indicate different behaviors say at the decent/bottom time/ascent portions of a dive. The algorithm then computes activity metrics within each dive segment. These activity metrics are based on the vectorized dynamic body acceleration (VeDBA), which is a metric of total movement, combining all three axes of the accelerometer. As it relates to the effort required for bodily motion, DBA has been shown to relate well to work performed (Qasem et al. 2012; Wilson et al. 2006), and variation in DBA can be indicative of changes in activity (Halsey et al. 2011). The mean VeDBA is used to estimate the total swim effort within a dive segment. Peaks in VeDBA exceeding a selected threshold are considered to indicate bursts in activity; these peaks were tallied to provide an "activity count" for each dive segment. These activity counts should relate to bursts of activity such as prey capture attempts (this will be our primary metric of interest). In addition to swim effort and activity count, starting depth, ending depth, and duration are recorded for each dive segment.

We ran the DSA algorithm blinded; we sent sensor data (depth and accelerometry) to our Wildlife Computers collaborator who ran the algorithm on the data set and returned dive summary statistics. We then matched the dive segments identified by the algorithm to our video-based behavior classification data. For this pilot analysis, we applied the algorithm to data sets matching four different videos showing very different behaviors: A) primarily transiting between locations, B) actively foraging over varied depths, C) actively foraging at consistent depth, D) sleeping underwater.

To assess the algorithm's performance, we compared activity counts in dive segments with and without key behaviors and calculated the correlation between activity counts and time spent in key behaviors. In initial data exploration, it was clear that the energy/motion associated with initiating an upward swim to the surface often generated high activity counts. Thus, to avoid confounding between diving and foraging activity, we removed segment 1 (typically the descent phase) and segment 5 (typically the ascent phase) from each dive, so that we only considered performance in detecting prey capture activity during the bottom time of a dive. Key behaviors associated with bottom time were classified as follows:

- Sleeping – times when the seal in not moving would be expected to show a near zero activity count – this category included all time periods classified as either "sleeping" or "quit moving" in the video ethogram.
- General Swimming – swimming either in transit or in search of food might be expected to generate some activity counts, though hopefully a low number distinguishable from prey capture activity – this category included all time periods classified as either "searching," "passing fish," "bothered by a predator," or "transiting" in the video ethogram.
- Prey Capture – attempts to capture prey should entail the greatest burst of movement, and would be expected to generate the highest activity count – this category included all time periods classified as either "rooting," "chasing," "attempting to catch prey," or "catching prey" in the video ethogram.

Table 2. Definitions of behavior codes used in ethogram analysis from seal-cam videos.

Behavior code	Description	
	Foraging Behaviors	
F	Foraging — Look/Search for Prey	swimming near the bottom or reef, head looks side to side
R	Foraging — Root for prey	root/dig for prey on bottom or in coral
C	Foraging — Chase prey	swim after prey in water column
A	Foraging — Attempt — attempt catching prey	the specific attempt to grab/capture/bite a prey item
X1	Catch Prey Item — suspected	seal appears to have caught prey
X2	Catch Prey Item — confirmed visually	seal caught prey — visually obvious b/c prey seen in mouth or bitten
X3	Catch Prey Item — confirmed by audio	seal caught prey — not visually obvious, but crunching noted
E	Foraging — Eat prey	seal eating prey — especially for larger prey at surface
	General Movement	
D	Down/Diving	body oriented downward, moving toward bottom
Q	Quit moving/Stationary	holding still
T	Transit	moving/swimming
U	Up/Surfacing	body oriented and moving toward surface or at surface
	Resting Behaviors	
S	Nap/Sleep	seal underwater, not swimming, typically moves with current
O	Hauled out	seal on land (use this code for any on-land observations)
	Interactive / Other Behaviors	
I	Interaction (with other seal)	directed looking, following, contacting other seals
B	Bothered/Escorted by other predator	predator following/approaching foraging seal
V	Vocalizing	making vocal noises, may be more apparent from audio than video
Z	Other — specify in notes	use this for any remarkable behavior not captured by other codes
	Potential Prey Encountered	
P1	Pass prey/fish — 1–5	any fish passed while swimming
P2	Pass prey/fish — 5–10	any fish passed while swimming
P3	Pass prey/fish — 10–20	any fish passed while swimming
P4	Pass prey/fish — 20–50	any fish passed while swimming
P5	Prey/fish — 50+	any fish passed while swimming

Behavior code	Description	
	Habitat Variables	
H1	Habitat — sand, even	benthic habitat primarily sand flats
H2	Habitat — sand, with relief	benthic habitat sandy, but topography is apparent
H3	Habitat — sand, with rocks/coral	benthic habitat is sand mixed with rock or coral
H4	Habitat — hard, even	benthic habitat is hard bottom/“pavement”
H5	Habitat — hard, with relief	benthic habitat is hard bottom/“pavement,” with topography
H6	Habitat — hard, with rocks/coral	benthic habitat is hard bottom, but with rock or coral mixed in
H7	Habitat — midwater (bottom not seen)	bottom is not apparent

RESULTS

Objective 1) Classify monk seal behavior from video

The behavioral classification using the BORIS software allowed us to generate ethograms that were useful in preliminary data exploration (Figure 2). Once combined with sensor data, the coded behaviors allowed us to examine the movement and energetic signatures of each behavioral category. The ethogram analysis from videos showed considerable variation among individual seals. While few generalizations were possible from such a small sample set, one interesting pattern emerged that the behavior of chasing after prey was almost entirely confined to the juvenile seals in this study. Juvenile seals spent up to 18% of their foraging/search time chasing prey, whereas this behavior was virtually unseen in the subadult-adult seals (Figure 3). Using ODBA as a metric of energetic intensity, we saw that chasing was approximately 50% more energetically intensive than rooting to target prey (which had a similar average ODBA to general swimming in transit; Figure 4). For comparison, the average ODBA for sleeping was approximately 30% that of swimming or rooting (Figure 4).

Objective 2) Use accelerometry metrics to distinguish activities

Exploration of accelerometry data showed relatively strong distinctions between some key behavioral categories, particularly sleeping, transiting, and prey capture activity (Figures 5–7).

- Sleep—was one of the most distinguishable behaviors in the accelerometry signal. It was marked by very stable segments in all axes (low SD, Table 3), punctuated by periods of greater motion while surfacing and diving down to the sleeping location (Dives 1–3 in Figure 7).
- Prey capture activity—appeared as bursts of activity, typically most pronounced in the Y and Y accelerometer axes, leading to peaks in ODBA and high SD in both raw accelerometer readings and the ODBA metric (Table 3). Here we are including rooting, chasing, and prey capture attempts in the umbrella term for behaviors associated with "prey capture activity." While all of these behavior codes were associated with highly dynamic accelerometer signals, they were not readily distinguishable (Dives 4–5 in Figure 7).
- Transit—dives with swimming, but no/little prey capture activity could be distinguished by relatively low standard deviation in the Y accelerometer axis, indicating a relatively consistent pitch while swimming (Table 3; Dives 6–8 in Figure 5). But note, this accelerometer pattern was similar between transit dives and dive portions that included bottom searching behavior without prey capture attempts (most of Dive 4 in Figure 7), thus the depth and/or dive shape become important considerations in making these finer distinctions.

With our classification rules based on standard deviation of depth and the X accelerometer reading, we were successfully able to identify sleeping with 88.54% accuracy relative to the video analysis (Table 4). Much of the discrepancy was due to false negatives in which the video ethogram indicated sleep and the instrument statistics did not. These false negatives typically occurred at the beginning and end of sleep bouts where the accelerometer signal (bottom graph, Figure 8) showed the seal to be relatively active (orange in the middle graph, Figure 8), however the human-classified, video-based ethogram still indicated sleeping (top graph, Figure 8). These beginning/end discrepancies are likely related to

a. body movement that continues after a seal may have visually settled into a sleeping location,
b. body movement that is initiated before the seal is seen to make movement away from the sleeping location, or
c. slower reaction of the human classifier versus the electronic signals.

The video validation analysis for R7AW indicated that animal probably slept for 6 min at a shallow depth (~6 m) that was not picked up in the sensor analysis. We suspect that the reason is because the wave surge at 6 m moved the animal enough to keep the sway accelerometer standard deviation above the 0.08 threshold. This indicates that behavioral differences between animals, and likely even within animals between trips will give varying results for a particular set of criteria and it will always be a trade-off to minimize false negatives and false positives. Applying the sleep classification to the entire instrument deployment of each seal indicated that Y2JU slept for nearly 13 h over a 98-h deployment at depths greater than 15 m, while other seals spent the majority of their rest time at shallower depths (Figure 9).

Objective 3) Calculate pitch for distinguishing foraging events/prey capture

The standard deviations of most accelerometer metrics were large relative to the difference in the means between behavioral categories (Table 3), indicating it would be very difficult to distinguish between most behaviors based on accelerometer data alone. The pitch metric showed considerable overlap between behavioral categories (Figure 10). While prey capture attempts and descent tended to show the most head-down pitches, even these were seldom near the 70° threshold suggested by Wilson et al. 2017 as an indicator of foraging behavior. The more general rooting category (which describes the head-down hunting for prey, which may be more extended than a single discernable capture attempt) was not well characterized by low-angled pitch. In fact, using the pitch metric would miss nearly all rooting behavior using a threshold of 70°, and still as much as 80% using a much-relaxed threshold of 45° (Table 5).

Objective 4) Test algorithms for distinguishing foraging events/prey capture

Not all dives were detected by the Wildlife Computers algorithm. Because the algorithm employed a 5-m threshold for defining dives, very shallow dives went undetected (Figure 11, video A). Additionally, running the Wildlife Computers algorithm on CATS camera output seemed to cause some difficulties in aligning timestamps, so that the algorithm detected and analyzed some partial dives but failed to detect some full dives (Figure 11, videos C and D). This misalignment caused considerable manual post-processing to realign the algorithm-output dive segments with our video ethogram data. For this, we relied heavily on the starting and ending depth output in the description of each dive segment.

Initial analysis showed that the seal's body movement associated with turning from benthic swimming toward the surface, and the initial propulsion to start an ascent, often generated high activity counts. Over all analyzed dive segments, 13 of 30 segments with at least 1 activity count were ascent phases of dives, including 2 of the top 5 activity counts. Because ascent was not our target behavior of interest, we separated these from the data set for the remaining analysis.

Once we limited our analysis to dive segments containing bottom time, the algorithm showed promise for detecting activity associated with prey capture behaviors. As above, we are including rooting, chasing, and discernable prey-capture attempts in the broader category of prey capture behaviors as these all involved high activity rates, but could not be distinguished from one another. There was correlation of $r = 0.889$ between the activity count and the number of seconds of prey capture behavior contained in a dive segment (Table 6). General swimming behavior (including searching and transiting) also showed positive correlation with activity count. Particularly at lower activity counts (1–5), several segments had activities counted where general swimming, but no prey capture behavior, occurred (Table 6). Total segment duration also positively correlated with activity count.

Table 3. Summary statistics describe accelerometer (Acc) readings and derived metrics associated with different behavioral classes in Hawaiian monk seals.

	All Seals								
	Root	**Search**	**Chase**	**Attempt**	**Conf. Catch**	**Ascent**	**Descent**	**Sleep**	**Transit**
AccXmean*	1.19	0.92	1.61	1.74	1.92	0.10	2.48	−1.10	−1.16
AccXsd	4.74	3.03	3.99	5.37	4.34	3.85	6.55	3.10	3.02
AccYmean*	0.43	−0.06	0.78	0.24	0.91	−0.49	0.19	2.51	−0.41
AccYsd	4.20	3.20	4.17	4.64	4.42	3.26	2.96	6.91	3.11
AccZmean*	−6.38	−8.84	−7.67	−5.03	−7.23	−8.43	−5.51	−2.13	−8.56
AccZsd	4.62	2.18	3.71	5.00	3.51	2.42	3.93	4.96	2.71
ODBA	0.08	0.09	0.14	0.14	0.11	0.10	0.08	0.03	0.07
ODBAsd	0.12	0.10	0.20	0.14	0.16	0.11	0.10	0.07	0.09
Pitch**	−19.14	−9.97	−11.48	−27.93	−16.65	−5.28	−42.62	−5.55	−10.07
Pitchsd	24.90	16.71	24.93	25.39	26.47	24.02	27.32	19.00	16.72
Roll**	−3.23	−3.94	−3.93	−2.59	−12.29	−5.32	−6.46	−46.32	−2.48
Rollsd	52.83	25.01	41.34	64.53	40.97	26.44	54.10	65.63	28.11

* metrics presented in units of gravitational force (g)

** metrics presented in angular degrees

Table 4. The agreement / disagreement rates are shown for the sleep classifier based on depth and accelerometry versus classified according to seal-cam videos.

The sensor-based classifier detected sleep based on low standard deviations for depth and Y-axis acceleration.

	Y2JU Video	**YR29 Video[c]**	**R7AW Video[d]**
Video-classified Sleep (min)	47.57	0.78	25.87
AccY & Depth-Classified Sleep (min)	42.27	0.12	0
% Agreement	88.54%	0.00%	0.00%
Agreement	42.12	0.00	0
False Negative[a]	5.45	0.12	25.87
False Positive[b]	0.15	0.78	0

[a]Video Ethogram indicated sleep, Acc analysis did not

[b]Acc analysis indicated sleep, Video Ethogram did not

[c]A single session at 3-m depth

[d]20 minutes occurs on land, ~6 min looks like an actual rest at ~6 m

Table 5. Seals spent little of their rooting time with bodies inclined at high angles.

This table shows that low percentages of seals' rooting time would have been correctly classified based on pitch thresholds either at 45° or 70°.

	Total Root (s)	Root >45°		Root >70°	
		s	%	s	%
Y2JU	1188	271.22	23%	46.68	4%
YR29	686	113.4	17%	21.24	3%
R7AW	958	175.48	18%	33.92	4%
RJ08	3025	399.26	13%	84.96	3%
RJ40	550	50.2	9%	16.55	3%
RKB0	863	137.1	16%	21.85	3%

Table 6. Results of the Wildlife Computers activity detector algorithm show correlation of activity counts with varied classes of Hawaiian monk seals behavior from seal-cam coding.

Prey Capture activity includes several of the seal-cam codes for active foraging behavior (rooting, chasing, prey capture attempts), while Other/General activity includes swimming in transit or searching for prey.

	Segment Duration	Prey Capture	Other/ General	Sleep
Correlation with Activity Count	0.358	0.889	0.371	−0.074
Zero Activity Count (0)				
Mean (s)	18.533	0.733	13.000	1.733
SD	18.635	2.840	20.657	5.106
Segments w/Behav		1	9	2
Segments w/o Behav		14	6	13
Low Activity Count (1–5)				
Mean (s)	133.429	3.571	80.857	46.214
SD	113.824	8.036	85.722	113.099
Segments w/Behav		3	11	4
Segments w/o Behav		11	3	10
Moderate - High Activity Count (7–23)				
Mean (s)	128.750	40.500	88.248	0.000
SD	57.877	35.641	34.191	0.000
Segments w/Behav		4	4	0
Segments w/o Behav		0	0	4

DISCUSSION

Objective 1) Classify monk seal behavior from video

The BORIS software offered a substantial improvement in efficiency over previous protocols for entering ethogram data from seal-cam videos. While previous protocols required repeatedly pausing the video to manually type timestamps and behavior codes into a spreadsheet, BORIS allowed for seamless entry of single-letter codes while the video played. The output csv table automatically combined time stamps, animal ID, and behavior codes that could easily be combined with the sensor data generated on the same timeline.

Youthful exuberance vs the wisdom of age—Even with this modest sample of seals, we were able to make some valuable comparisons and contrasts between animals. The most apparent difference was in foraging strategies and energy use between juveniles and older seals. Juveniles were far more likely to exhibit prey-chasing behavior. This sometimes did result in prey capture, but not always, and did not appear to necessarily be a more profitable strategy than the more common rooting behavior. The analysis of ODBA showed that this behavior was more energetically costly than rooting, so it might be that older seals discard this behavior as they become more efficient at rooting for prey. Inefficient foraging techniques in juvenile seals could point to one of the underlying causes of failure to thrive and poor survival in the juvenile age classes (Baker and Thompson 2007). The chasing behavior was not noted in previous seal-cam analysis (Parrish et al. 2000; Wilson et al. 2017a) which included almost entirely adult samples. It is possible that this behavior was not noted until our recent focus on juvenile animals, or it could be a difference in classification / coding schemes. Previous videos could be revisited with this new code in mind to generate a larger data set for juvenile-adult comparisons.

Competing predators, not just for the NWHI—Interspecific competition is thought to be one factor underlying the nutritional limitation and poor body condition that is commonly seen in juvenile seals in the NWHI (Parrish et al. 2008). Seal-mounted videos have shown that predatory fish (most commonly jacks, *Caranx* spp., and sharks, *Carcharhinus* spp.) travel with foraging seals to exploit the seals' superior ability to flush cryptic prey from benthic habitats (Parrish et al. 2008). While escorts by such competitors were common in the NWHI (seals were followed by predatory fish for 17% of their foraging time; Parrish et al. 2008), they are much more rare in the MHI (few escorts observed by Wilson et al. 2017a) where predatory fish populations have been decreased by human fishing pressure. However, in our data set, seals in both regions interacted with sharks. Several possible reasons could account for this difference, not least of which is the small sample size of the current pilot study. Still, it merits further investigation to determine whether the regional differences noticed in the Parrish et al. 2008 and Wilson et al 2017a studies might have been confounded by the temporal lag between the instrument deployments. It is possible that conditions could have varied in either region during the10-15 years between these previous studies. Further, past findings have suggested that juvenile monk seals are particularly encumbered by attending predators (Parrish et al. 2008), so our study may be more likely to detect this phenomenon in the main Hawaiian Islands given our recent juvenile-focused sampling scheme, and the lack of juvenile representation in previous MHI seal-cam studies (Wilson et al. 2017a).

Objective 2) Use accelerometry metrics to distinguish activities

The stillness of sleeping seals created a readily distinguishable pattern in accelerometry data, with all axes showing very low variability, and the sway (Y-axis) being particularly informative. When we applied the sleep detector to the full duration of sensor data for each seal, we saw that the depth at which a given seal slept varied with that seals general depth profiles. Y2JU, who traveled far from shore and typically made deeper dives, also slept at depths of 50–80 m reflecting the habitat he was utilizing. RJ40, the other juvenile to travel long distances to deeper foraging sites was not observed to sleep on any of her trips (indicating substantial stamina). Other seals frequented shallower territory, and likewise the majority of their sleeping activity was <15 m deep. While we did not show any consistent proportion of sleeping activity either by depth or by foraging trip duration, this video- and sensor-informed analysis helps to understand the behaviors likely represented in different dive patterns.

Objective 3) Calculate pitch for distinguishing foraging events/prey capture

The pitch metric calculated from the accelerometer was highly variable and not as steep as found in one previous Hawaiian monk seal accelerometry study (Wilson et al. 2006). We found that pitch was unlikely to provide a clear indicator of monk seal foraging activity. This was surprising given the description of reliable head-down foraging posture mentioned in both of the previous seal-cam studies (Parrish et al. 2000; Wilson et al. 2017a), so we examine several potential reasons for this difference. Could animals in our study, especially the juveniles, be utilizing different foraging strategies involving different body posture? This is an unlikely explanation, as we specifically evaluated pitch for rooting and prey capture behaviors where high angle pitch is typical. Could different instruments (CATS vs OpenTags) or different placement (given different instrument package size/arrangement) have impacted the pitch detected in our study vs previous? This explanation is possible, and it could be examined further through simulations. Could differences in video-based behavior classification protocols have impacted the comparability of the data? This explanation is possible; for example, the degree to which video analysts used pitch as a visual cue for defining rooting behavior could have varied between studies. This could be addressed through cross validation between data sets and analysts.

Objective 4) Test algorithms for distinguishing foraging events/prey capture

The Wildlife Computers algorithm showed promising correlation between activity count and prey-capture activity ($r=0.88$ within bottom segments of dives). As this was a directional correlation, but not a precise relationship between a given amount of prey-capture activity and a specific activity count, the algorithm should be considered an index of foraging activity, but not a quantification. While the highest activity counts most reliably classified prey-capture activity, lower values (1-5) seemed unreliably related to foraging or any other activity. Further exploration may be useful in determining a certain threshold beyond which activity counts can be attributed reliably to prey-capture activity.

At this pilot stage in the project, we experienced some technical difficulties applying the Wildlife Computers algorithm to the CATS sensor data. This may have been due to a difference in formatting or other issues related to providing the algorithm only a subset of the data (for which we had matched video segments). As a result, the output required significant post-processing to realign the dive segments identified by the algorithm with the appropriate timestamp, sensor, and behavioral data from the seal-cam data set. The Wildlife Computers team has identified certain recoding procedures that may help better align the timestamps and avoid this post-processing.

FUTURE DIRECTIONS

After the pilot analysis presented here, we have developed a short list of priority future directions to improve Hawaiian monk seal foraging research utilizing accelerometry (and other high-resolution sensors).

- *Continue to expand sample sizes to improve power for inference*
  Given the high individual variability among monk seals, additional samples will be necessary to make strong inferences regarding differences between age classes or geographic regions. This is particularly relevant for juvenile samples for comparison the MHI and NWHI, given that juveniles had not previously be instrumented with cameras in the main islands (and only few had been instrumented with CritterCams in the NWHI). Further, additional sampling in which animals are instrumented in the MHI and NWHI within the same time frame (season or year) will be valuable for isolating geographic from temporal differences.

  A thorough cost-benefit analysis will be an important part of determining appropriate samples sizes for continuing studies. Many study subjects may be required to overcome existing levels of individual variation to make statistical inferences at high confidence levels. However, inferences valuable to conservation planning and species recovery may be possible with lower sample sizes than those considered statistically rigorous. Animal involvement in research will additionally need to weigh the cost and level of disturbance to the individual with the benefit of knowledge that might be gained. Incorporating multiple research facets into a single handling or instrument deployment (e.g. by taking epidemiological samples while animals are sedated for instrumentation, and trying to maximize sensors within a single instrument) can maximize the scientific benefit of each animal handling.

- *Cross-validate coding between studies*
  One important and efficient way to improve sample strength would be to combine data sets from previous CritterCam research efforts with current/future seal-cam deployments. An important step in joining the data sets would be to reanalyze a subset of previous footage to assess intercoder consistency. While classifying behavior from videos is a significant workload, this can be made more feasible with the help of volunteers or citizen science platforms. The abundance of footage accumulated across the Parrish, Wilson, and current studies could keep the public engaged for a long time to come (including in lulls between deployments where new data are not generated).

- *Digitize and archive previous CritterCam data*
  The Parrish CritterCam footage is an important data resource, and because it was collected years ago on Hi8 tapes, this footage has been largely inaccessible. Further, the longer this video media is stored, the more likely it becomes that this resource will become damaged and degraded. The HMSRP has plans to send these tapes for digitization at the end of FY20.

- *Test additional algorithms emerging/available from other companies*
  As high-resolution instruments become more popular, and onboard computing power makes compressed data transmission more feasible, several instrument companies have begun developing algorithms to summarize foraging behavior. Most make use of depth and accelerometry to classify animal activity and report a small set of statistics about each dive, rather than the large data set containing the full sensor data. SMRU and CATS are among companies working on such algorithms. The HMSRP has sent the same data set used in this project to SMRU to test their dive summary algorithm. To date, CATS has expressed interest in testing their algorithm, but has not had the capacity to do so with our data set. Our data set combining video and sensor data provides a powerful resource for validating behavior classification algorithms. We hope that by testing multiple competing algorithms, we can weigh the insights gained with each to make the best decisions for future instrument deployments and analyses for Hawaiian monk seals.

- *Consider developing Hawaiian monk seal-specific algorithms*
  Many (all) of the behavior classification or dive summary algorithms available through commercial instrument companies have been developed based on other species. This does not mean they cannot be useful monk seals; certain characteristics like bursts of activity associated with prey capture activity are likely to be relatively consistent among taxa. However, it is worth considering developing a monk seal-specific algorithm to maximize accuracy in distinguishing key behaviors of interest to monk seal ecology. Such an effort would benefit from partnerships with data and/or computer scientists, and would likely require collaboration external to NOAA PIFSC. Artificial intelligence has potential for intricate pattern recognition tasks such as discern different accelerometry and depth patterns associated with varied behaviors. It is unclear, however, whether such an algorithm could run efficiently enough to be incorporated into future instruments. Any collaboration would necessarily need to include communication with instrument companies that could eventually implement an algorithm once designed.

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FIG 1

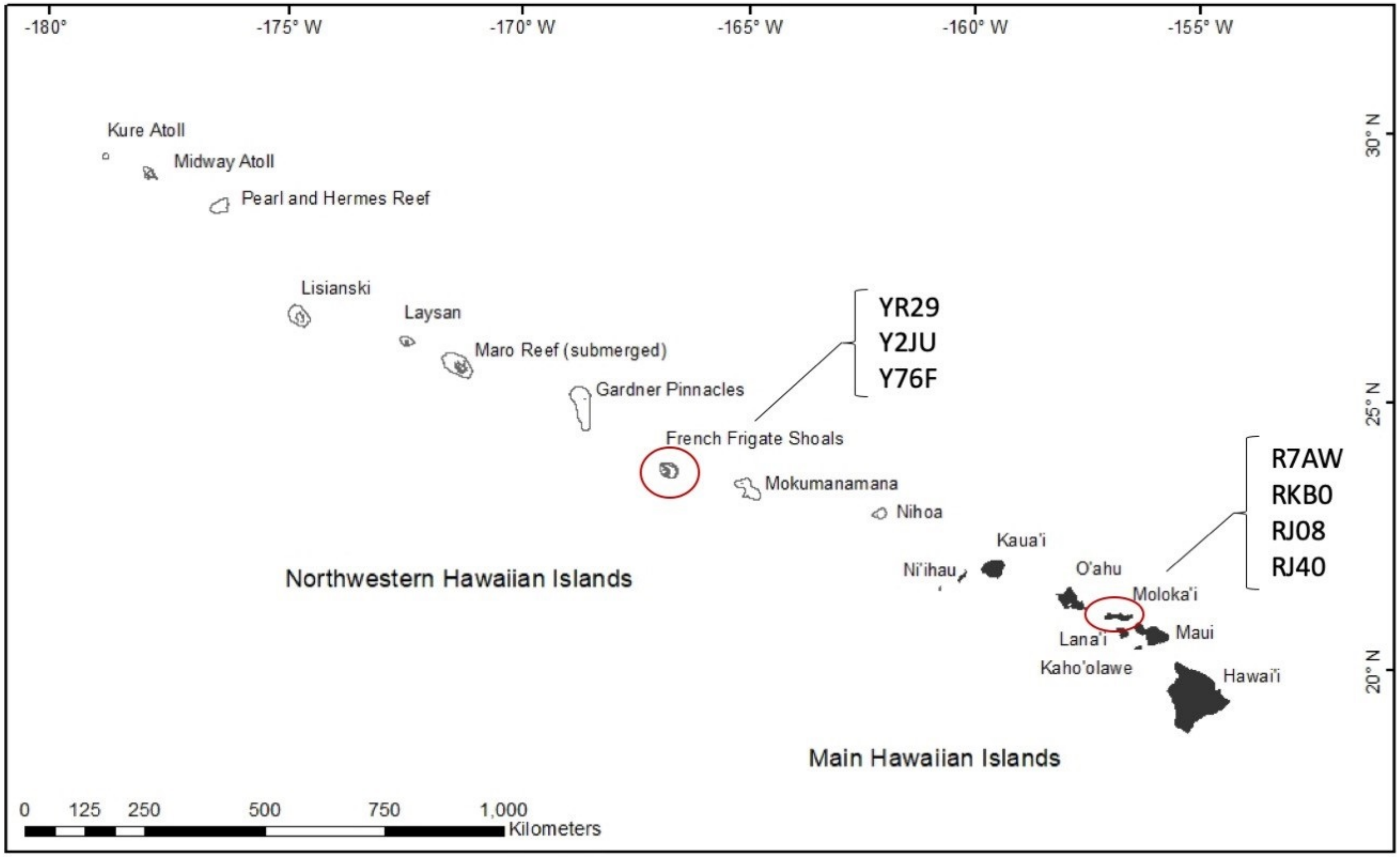


Figure 1. The map shows the Hawaiian Archipelago, constituting the entire of Hawaiian monk seals. Seals (indicated with 4 digit identifiers) from Molokai and French Frigate Shoals were selected for instrumentation with multi-sensor seal-cams in 2018–2019.

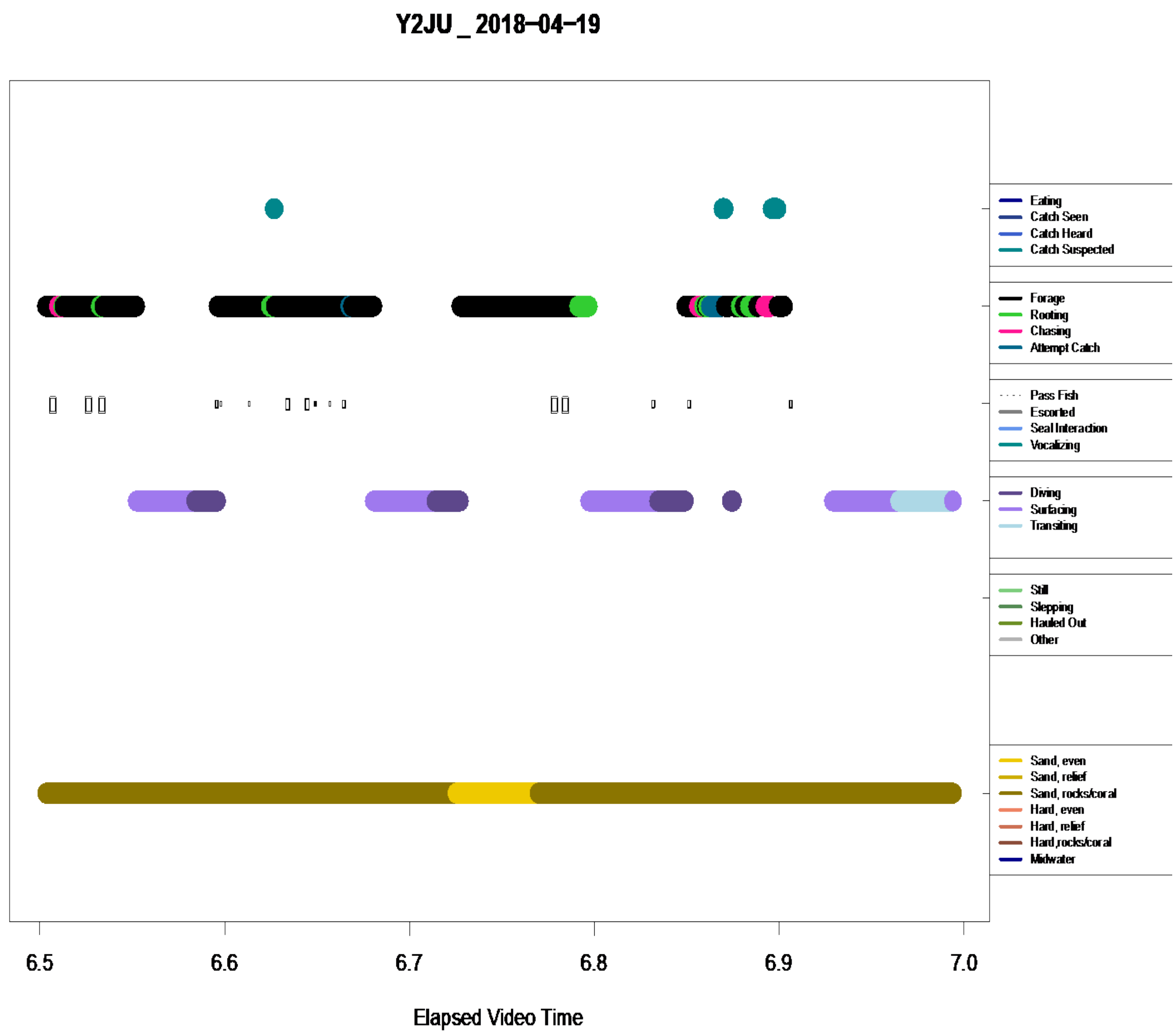


Figure 2. An example ethogram from a juvenile male Hawaiian monk seal, Y2JU, shows a wide variety of foraging behaviors. The behaviors coded in the seal-cam ethogram analysis formed the basis of comparison for behavior classifications using accelerometry metrics.

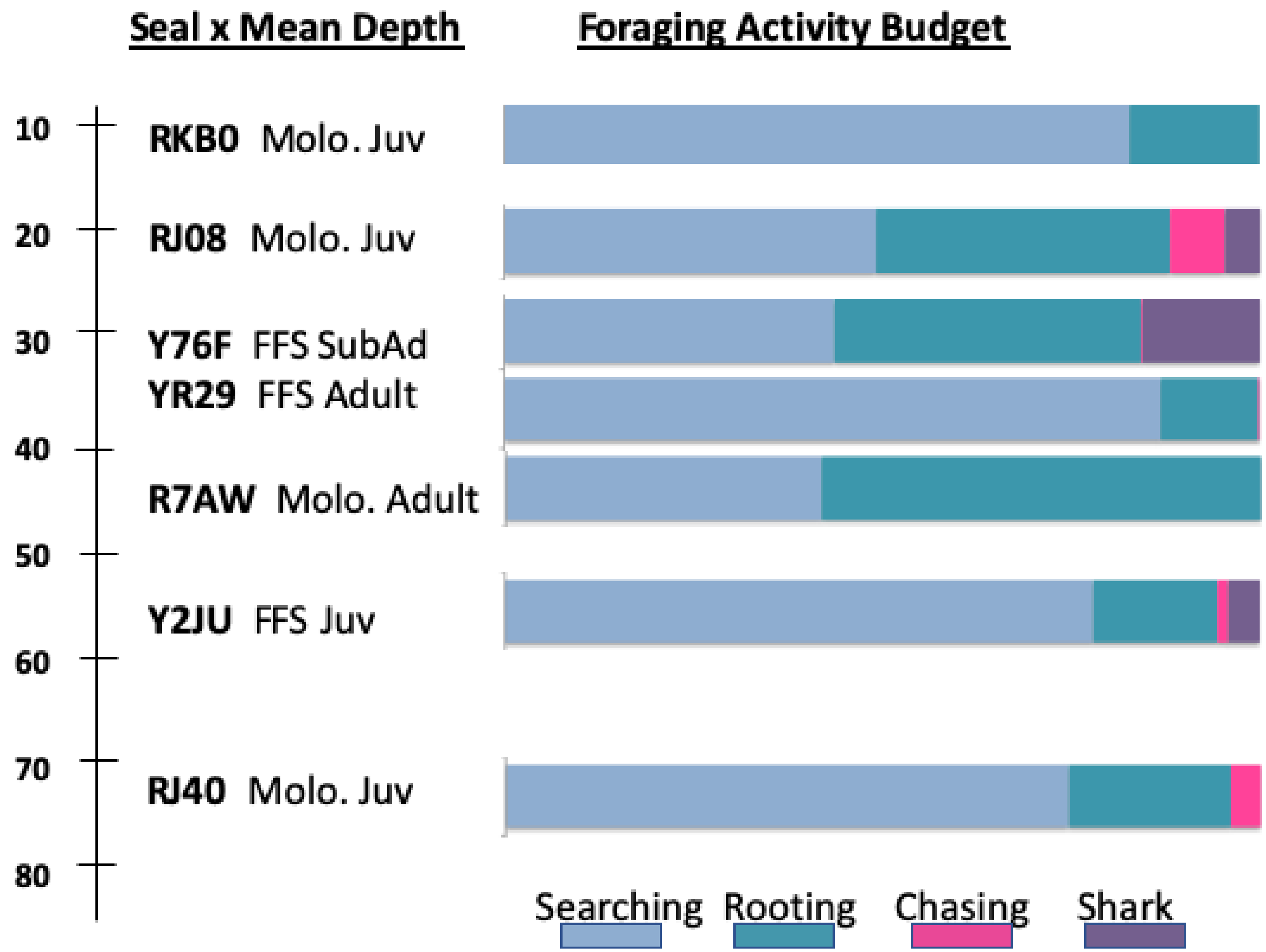


Figure 3. The activity budget chart shows the breakdown of how each Hawaiian monk seal in the seal-cam study (2018–2019) divided its foraging time. The Y-axis indicates the average dive depth (in meters) for each seal.

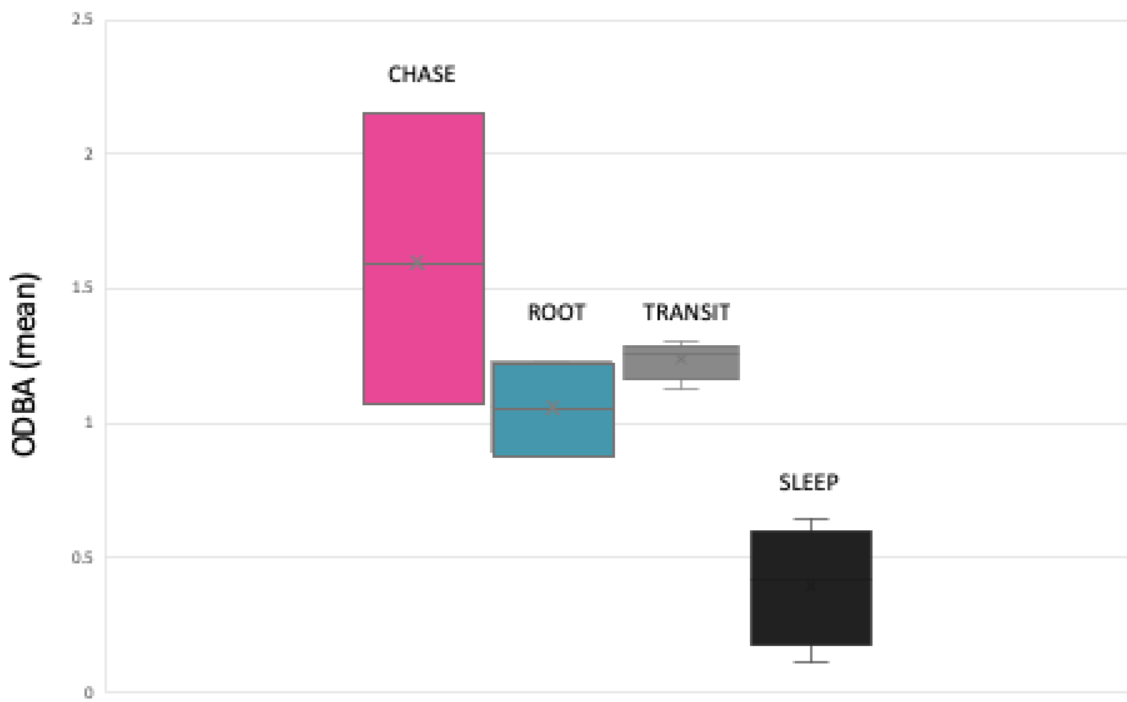


Figure 4. A box plot shows the variation in overall dynamic body acceleration (ODBA) associated with different behavioral classes. ODBA was calculated based on all axes of triaxial accelerometers, whereas the behavior was classified from seal-cam videos.

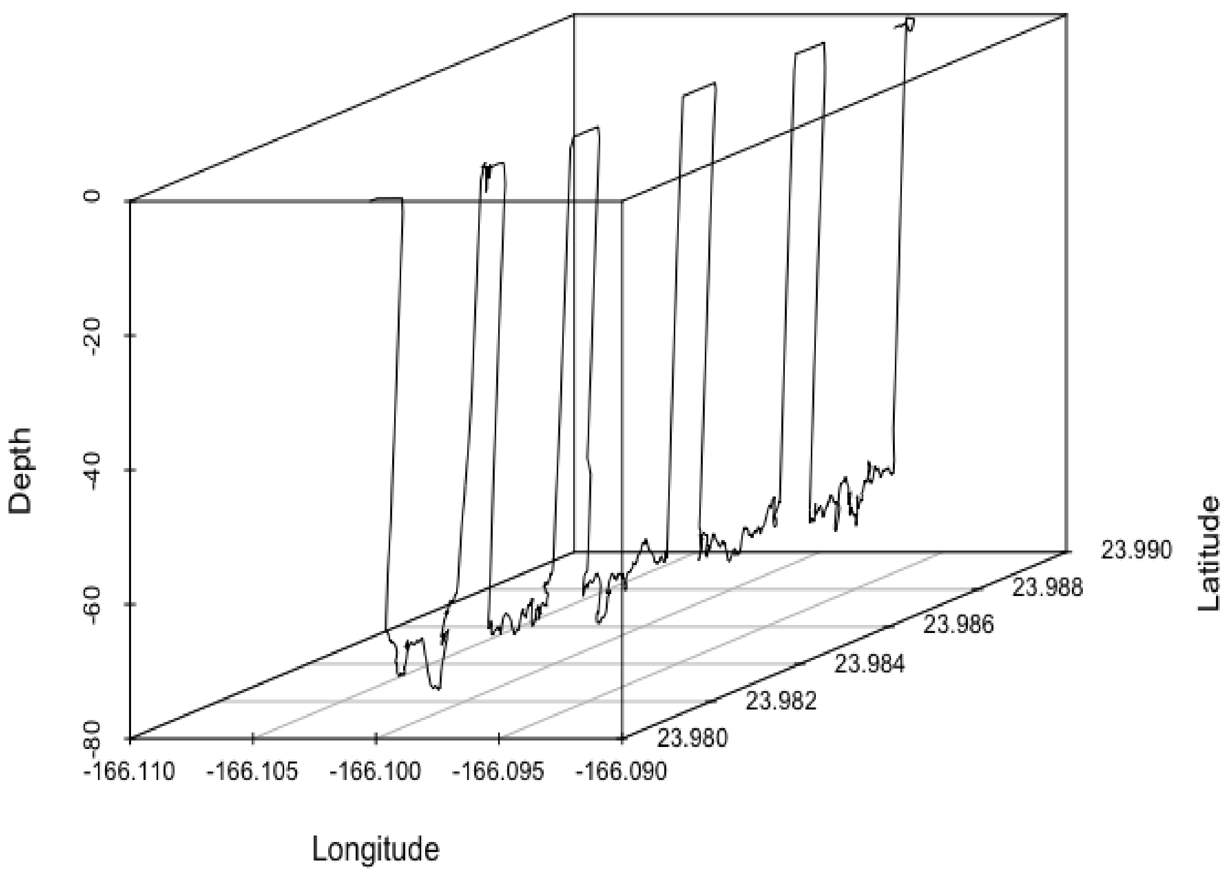


Figure 5. An exploratory plot shows a seal's dive pattern based on GPS location and depth sensor from the multi-sensor seal-cam.

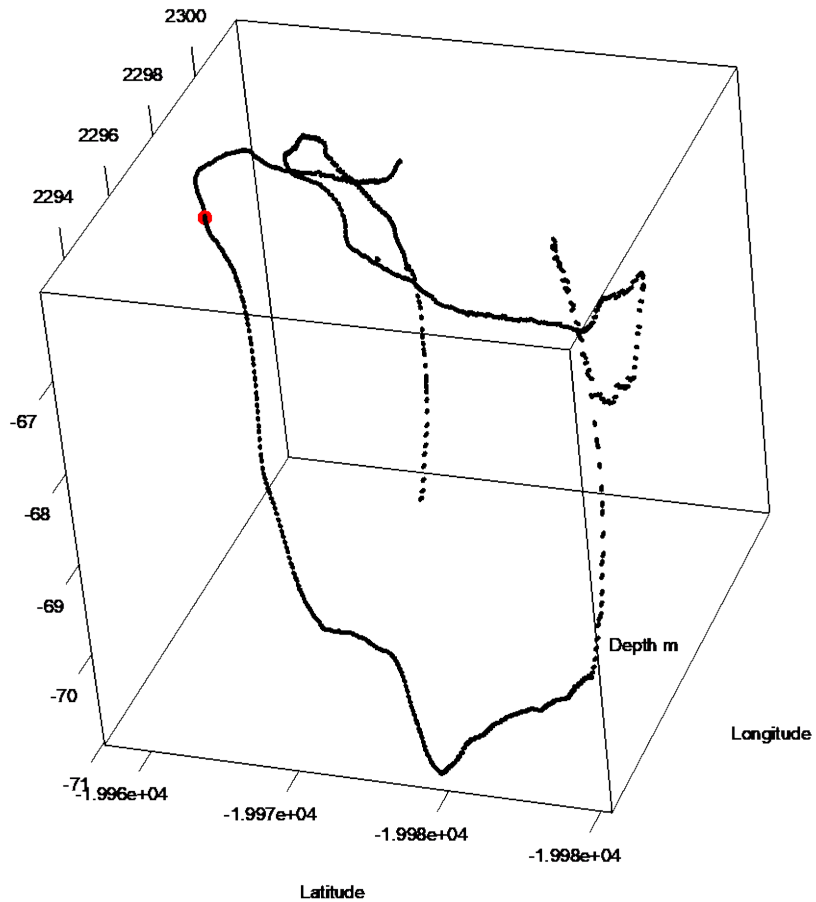


Figure 6. An exploratory plot shows a reconstruction of a seal's movement track based on GPS location, depth sensor, and with fine-scale movements inferred from accelerometer and magnetometer readings. This image is a zoomed in portion of the bottom time in the fifth dive from Figure 5. In an interactive format, the red dot would retrace the seal's movements based on the time stamps from the seal-cam data.

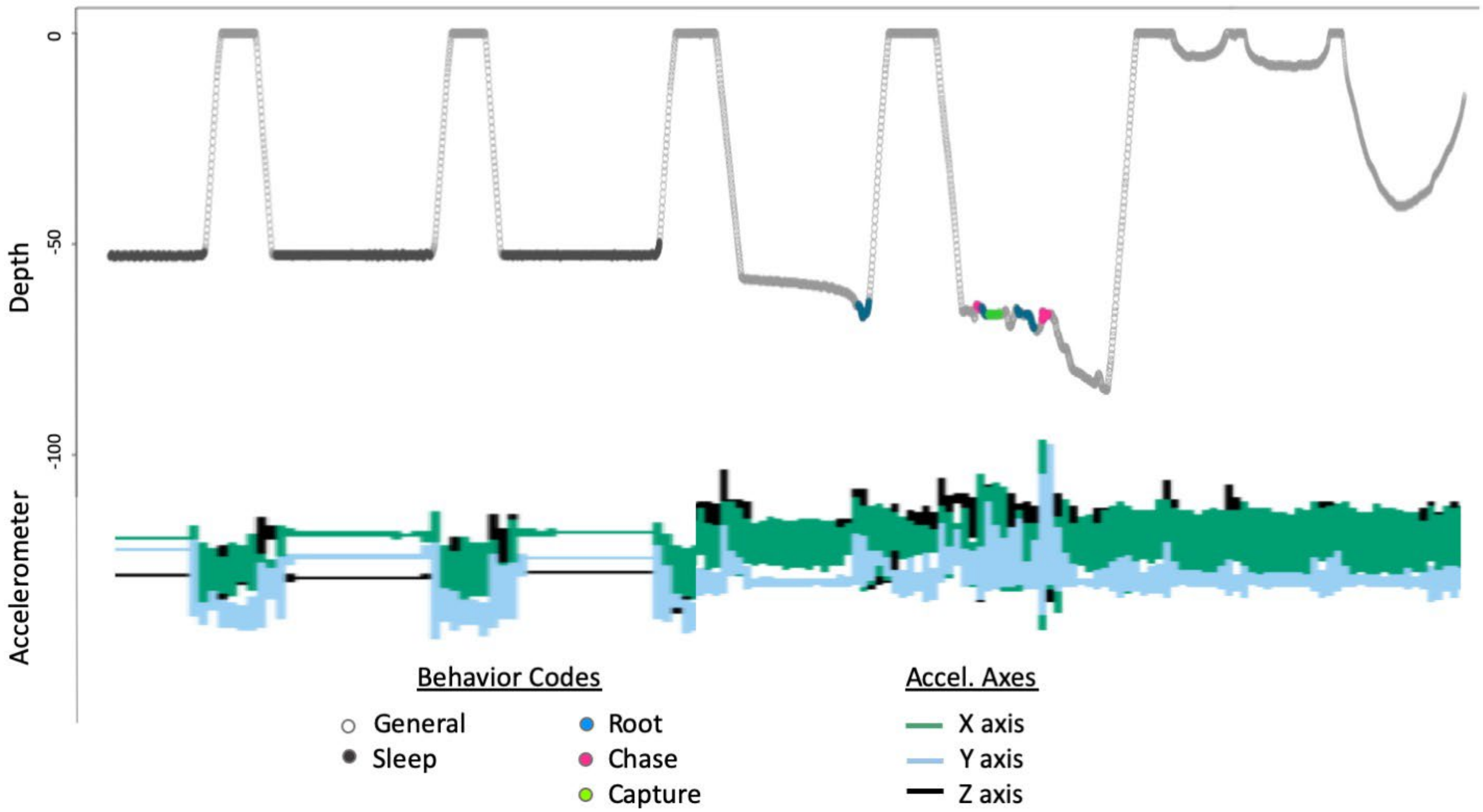


Figure 7. A composite plot shows several dives exhibiting varied behavioral classes, plotted by depth, and showing associated triaxial accelerometer signals. These are all dives from juvenile male Hawaiian monk seal Y2JU, and were among the same dives analyzed with the Wildlife Computers activity detector algorithm (Figure 9).

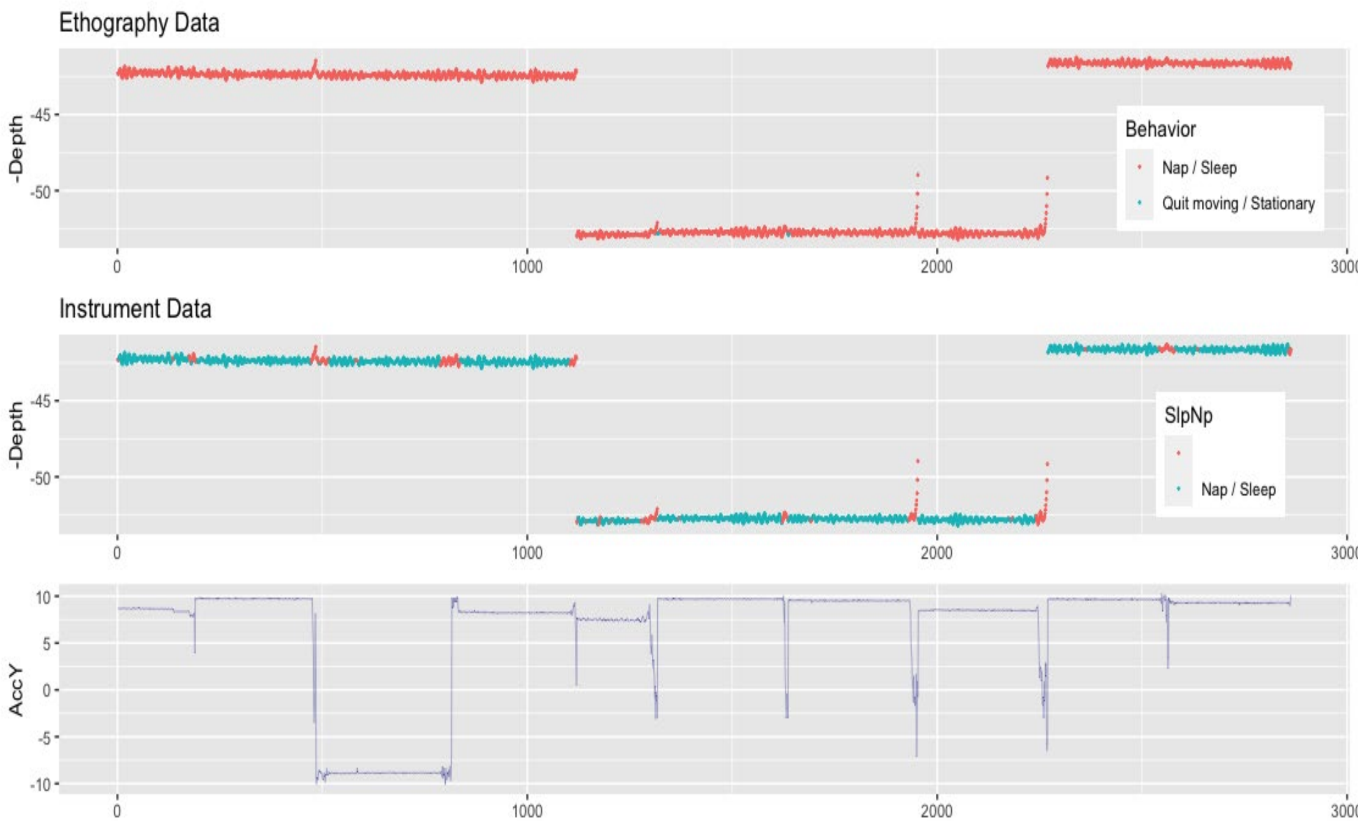
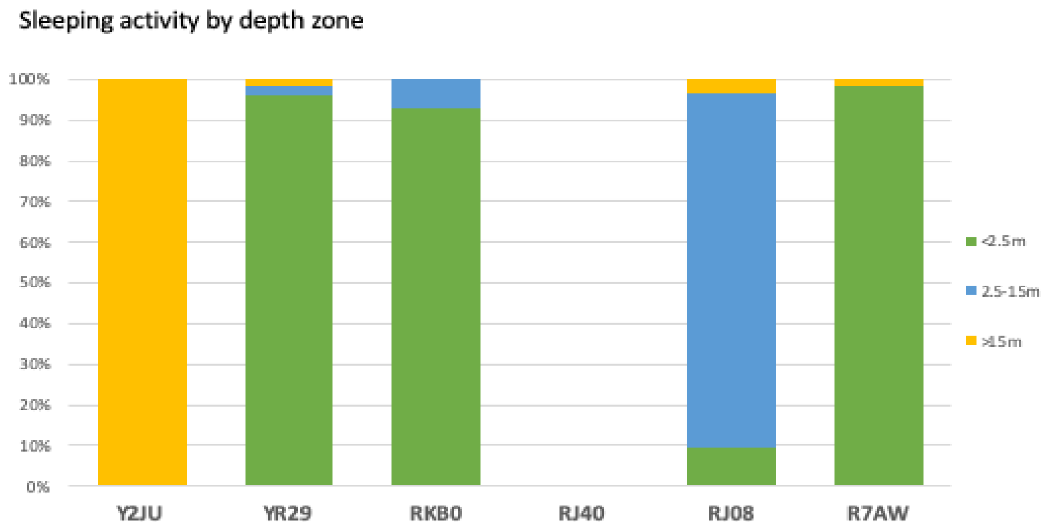


Figure 8. We provide a visual comparison of sleeping bouts classified by (A) human observers viewing seal-cam video, (B) by our sensor-based classifier, and (C) raw Y-axis acceleration signals. These graphs show a composite of several sleeping bouts, hence there is no other diving or behavior reflected between sleep bouts (as classified from seal-cam video). Plot B shows that some of the disagreement between classifiers includes periods at the end of sleep when animals begin to move upward.



	Y2JU	YR29	RKB0	RJ40	RJ08	R7AW
Sleep % Total	13.22%	5.33%	9.19%	0.00%	0.11%	40.04%
Sleep (min)	775.42	314.42	280.32	0.16	6.14	2263.44
Total Time (min)	5867.72	5903.74	3050.23	4348.41	5367.01	5653.52

Figure 9. Sleep budget plots show the proportion of Hawaiian monk seal sleeping activity taking place at varied depths. The proportion of sleep at each depth class was based on application of the sensor-based detector, applied to the full sensor deployment period.

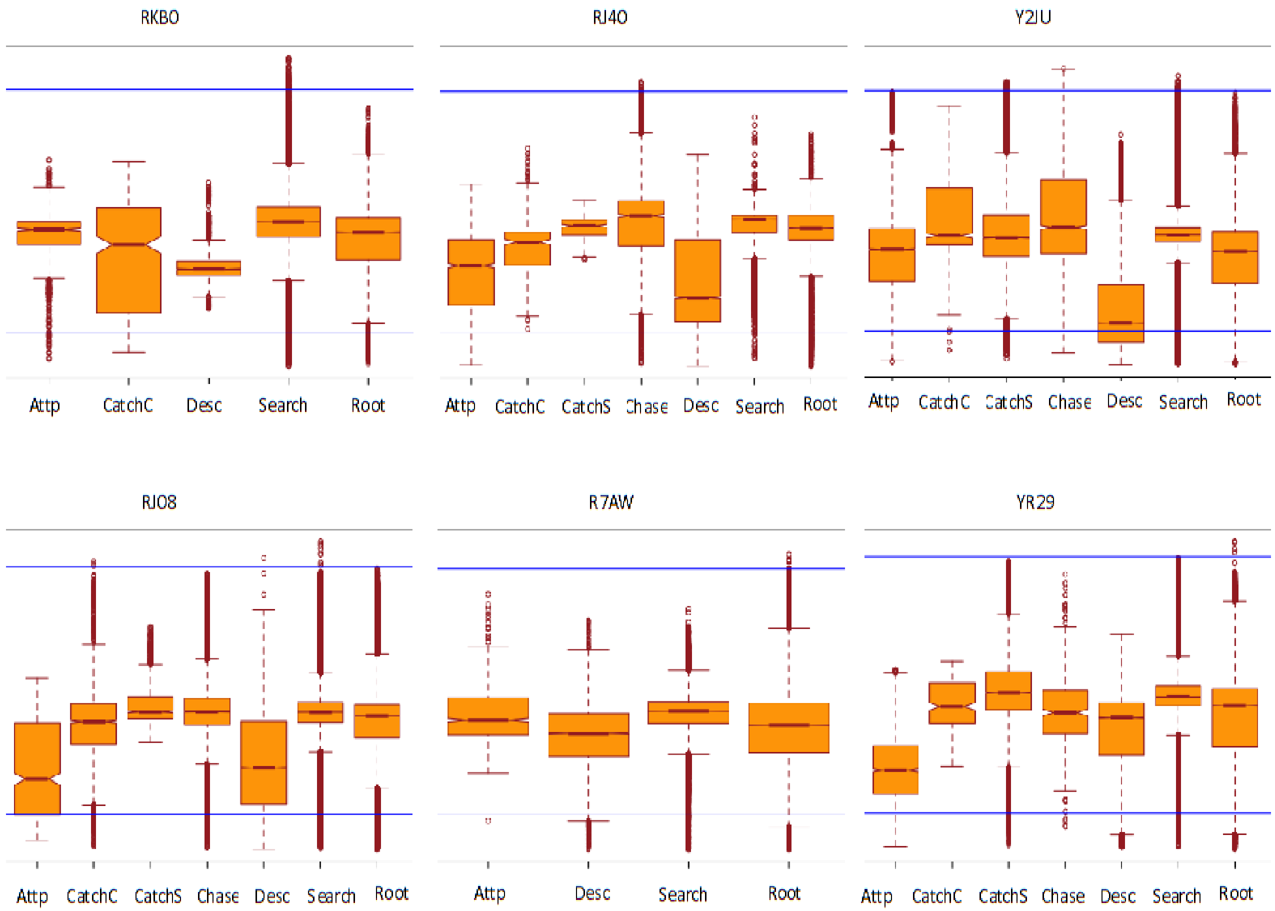


Figure 10. Box plots show the range of pitch measured for different behavioral classes for Hawaiian monk seals recorded with seal-cams (2018–2019). Behavior was classified from seal-cam video. Pitch was calculated from triaxial accelerometry. Blue lines indicate the suggested 70° threshold for Hawaiian monk seal prey-capture activity.

(Attp = Attempt, CatchC = Confirmed catch, CatchS = Suspected catch, Dec = Descend)

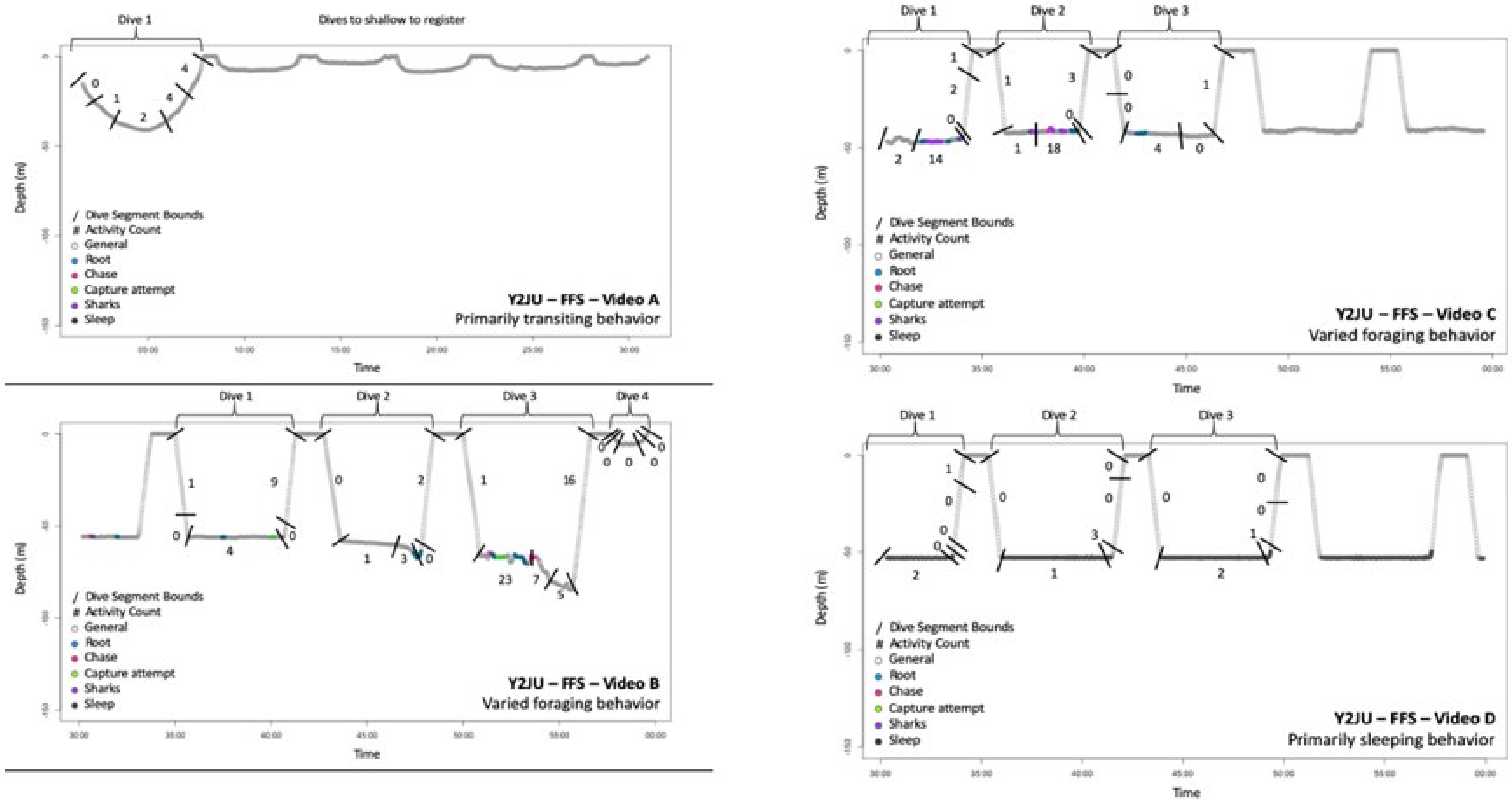


Figure 11. Dive plots show monk seal behaviors classified in seal-cam video footage (colors) and activity counts calculated from the Wildlife Computers activity detection algorithm (numbers). Sensor data associated with four different videos was used to test the algorithm in a variety of Hawaiian monk seal behavior scenarios; A) swimming in transit near the surface, B) foraging activity including prey capture with varied depth, C) foraging activity including prey capture with consistent depth, D) sleeping at depth.