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In search of an optimal bio-logger epoch and device combination for quantifying activity budgets in free-ranging cattle

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ABSTRACT

Precision livestock management incorporates new technologies, including bio-loggers, to remotely monitor livestock health and behavior. Despite the potential benefits in extensive cattle systems, limited adoption of these sensors has occurred potentially due to cost, technical, or processing challenges. We resampled high-resolution GPS and accelerometer data across multiple epochs (spanning 10 s to 15 min) to evaluate which combinations of devices, data features, and epochs might be considered optimal for assessing resting, grazing, travel, and rumination behavior in free-ranging cattle. We used random forest models to predict cattle behavior across the growing season to assess how variations in model accuracy were reflected in inference of activity budgets. Classification accuracy was greatest (>0.90) when GPS information was combined with at least one accelerometer metric. Epochs of 30–90 s provided the greatest classification accuracy, although epochs up to 300 s had similar classification accuracies, but with increased variability in accuracy. Classification accuracies decreased when we included rumination, but similarly had the greatest performance when both GPS and a full suite of accelerometer features was used (accuracy of ∼0.90). Average daily grazing time (8.3 h day^{-1}) was within 2 h across devices, epochs, and behavioral schemes. Rumination time was again similar across devices and epochs, averaging 6.5 h day^{-1}. Daily travel distance decreased by ∼4 km as the GPS fix interval increased from 10 s to 15 min. This study provides guidance for balancing fine-scale data collection with data processing and battery limitations for assessing cattle behaviors in extensive rangelands.

1. Introduction

Precision livestock management techniques, such as the use of bio-logging sensors including Global Positioning Systems (GPS) and accelerometers, have enormous promise for increasing welfare and production of livestock [1] by allowing producers to pivot from reactive to proactive decision-making [2]. In fact, the rapid increase in technology over the past several decades has led to numerous innovations in livestock management [3]. For example, in western North America, most beef cattle operations depend on vast rangelands—frequently including public lands across arid or semi-arid landscapes—with inherent difficulties in monitoring herds in these extensive systems [4]. However, technologies are adding insight into spatial patterns and behaviors, as well as health [5] and parturition [6] monitoring. Additionally, GPS-based virtual fences are being investigated for their role in excluding cattle from certain areas such as sensitive riparian habitats [7] or recently burned areas [8] and facilitating targeted grazing to create fire breaks in landscapes [9].

Despite the promise of precision livestock management, there have been challenges in widespread adoption of technologies, with evidence that implementation in extensive beef cattle operations has been lower than other sectors [10,11]. Some of the barriers to implementation for behavioral monitoring include the high up-front costs associated with purchasing commercial GPS or accelerometer units for large scale deployments [12]. Additionally, some commercial systems have proprietary methods for behavioral classification (e.g., [13,14]), which may limit flexibility in application and inference. As an alternative, custom-built loggers are often substantially cheaper and allow greater flexibility in processing techniques [15]; however, they also require greater technical knowledge which may reduce useability and adoption

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[12,16]. While GPS units, accelerometers, and similar sensors can provide detailed information on behavior and activities, they can also generate gigabytes to terabytes of data, providing challenges associated with processing and analyzing which also make them difficult to implement for researchers, let alone producers [17,18].

A potential option for improving usability of bio-logging technology is streamlining data collection by defining what parameters from various bio-loggers over what time intervals are required to accurately define specific behaviors in inferentially meaningful ways. For example, behavior metrics can be derived from GPS units by calculating velocity and relative angles between locations to derive various animal activities such as resting, foraging, and travelling [19]. However, GPS devices have a wide range of programmable fix rates (i.e., locations collected at intervals of minutes to days), and such variation can yield vastly different interpretations of metrics such as travel distance [20,21]. When the interval between fixes is longer, distances become too linear and underestimate the fluid and tortuous movement of animals; conversely short intervals between fixes often over-estimate tortuous movement due to error in the GPS locations [22,23]. Behavior metrics can be derived from accelerometers as acceleration signals along three axes and can be used alone, or in combination with GPS information. While accelerometer data are generally sampled at very high-resolution frequencies (e.g., 12 Hz), the raw data are usually summarized over time intervals (e.g., 30 s), or epochs, which can impact classification accuracy [24]. From an accelerometer standpoint, shorter epochs are thought to be better because there is less mixing of behavioral signals [25], but longer epochs (i.e., over several minutes) should not be dismissed without investigation as they may be sufficient for some animals, like cattle which typically move slowly, to achieve accurate results while reducing the load on data storage or transfer systems [26]. Therefore, using bio-logging sensors such as GPS and accelerometers in precision livestock management requires knowledge on the balance between retaining the most information to accurately derive behaviors while minimizing the influence of GPS error or accelerometer summarization, a long-standing challenge to broad implementation of these devices across precision agriculture and scientific research.

Here, we investigated varying epochs (i.e., interval of time over which raw data are aggregated; [25]) and how they influenced the accuracy of machine learning-based behavior classification derived from custom-built tracking devices on free-ranging cattle in extensive rangelands of the western North American Great Plains. We then extended our investigation into how varying epochs impact behavioral inferences. We focused on the influence of varying epochs on estimates of grazing animal activities such as foraging behavior, which has been previously linked to weight gains [27], ruminating, which is an indicator of health and forage characteristics [28,29], and distances travelled, which is influenced by variation in foraging conditions [30]. Our aim was to provide insight into the optimal epoch or range of epochs over which cattle behavior can be derived from GPS and accelerometers, to guide data collection and facilitate improved comparison across studies, as suggested by Anderson et al. [31]. Specifically, our objectives were to examine 1) classification accuracy using GPS units alone, accelerometers alone, and GPS units with accelerometers using either broad suite or a simplified set of acceleration metrics across different epochs, and 2) examine differences in behavior-specific time allocations and travel distances. Cattle are large, generally slow-moving ungulates, so we expected behaviors of interest (e.g., grazing) would be sufficiently identifiable at <2 minutes, given previous work comparing 5-min and 4-s estimates of grazing [27]. We also expected accelerometers to have overall greater behavioral classification accuracies given the amount of information obtained from tri-axial signals, but also to have the greatest decrease in accuracy as signals were averaged over increasingly greater epochs.

2. Materials and methods

2.1. Study location and collar deployment

This study was conducted from mid-May to early October 2020 and 2021 at the Central Plains Environmental Research station near Nunn, Colorado, which is part of the United States Department of Agriculture-Agricultural Research Service (USDA-ARS) Long-Term Agroecosystem Research network. The study site was located in the semi-arid shortgrass steppe ecosystem [32], and detailed characteristics of the site and surrounding rangelands are described in Augustine et al. [33,34]. Annual precipitation was 262 mm and 380 mm in 2020 and 2021, respectively [35]. We studied mixed British breed (e.g., Angus and Charolais) yearling steers that arrived at each year in mid-May at a mean liveweight of ~270 kg and grazed shortgrass rangeland until early October when they reached a liveweight of ~400 kg. In 2020, we collared 2 steers in each of 10 herds that consisted of 23–27 animals grazing within 130-ha paddocks for the entire growing season (mid-May–October) and collared 7 steers in each of two heard consisting of 122 animals rotated among five 130-ha paddocks over the growing season (34 collared steers in 2020). In 2021, we collared 2 or 3 steers in each of 12 herds of 23–27 steers grazing within 130-ha paddocks for the entire growing season, 6 steers in each of 2 herds of 60–66 steers grazing in 360-ha paddocks, and 7 steers in each of 2 herds of 107 animals rotated among four 130-ha paddocks over the growing season (56 collared steers in 2021).

Cattle collars were designed and assembled by research staff and included a GPS data logging device (model P-1, Columbus, Berlin, Germany) and a tri-axial accelerometer (model X-16, Gulf Coast Data Concepts, LLC, Waveland, MS, USA). Materials for collar construction cost approximately $360 per unit (Supplementary materials: Table A1). Location fixes were collected at a 1-s intervals (i.e., the GPS unit remained continuously connected to visible satellites) and differently corrected onboard (e.g., [19]); a configuration that allowed units to run for 44 continuous days on a 30 Ah lithium polymer battery. The tri-axial accelerometer measured acceleration in the X(surge), Y (sway) and Z (heave) axes at approximately 12 Hz. Accelerometers were powered by 5200 mAh lithium-ion battery packs with a run time of approximately 60 days and were configured and deployed as described in Brennan et al. [36]. Both devices stored data on microSD cards. Electronics were enclosed in a waterproof, high-impact resin case (model T4000, S3 Case Company, Jackson, WY, USA) which was fixed into an aluminum cradle attached to livestock neck belts, with the case and cradle hanging under the animal's neck. Buckles on both sides of the neck belts were oriented to allow adjustment for size, with collars fitted to ensure that a person's fingers could fit between the animal's neck and the inside of the collar (Fig. 1). Total weight of the collar with the cradle, case, and all contents was 1.8 kg.

At the end of June and mid-August, batteries were replaced when cattle were gathered for weighing. Collared steers were checked multiple times each week to confirm that the collars were still attached. Dropped collars were retrieved as soon as possible and rebuilt, if necessary, before being redeployed, and data from periods when the collars were on the ground were removed from analyses. Fixes from dropped collars were used to estimate stationary error of GPS units, whereby we used the mean location for each dropped collar as the location of the collar, then calculated the distance of each fix from the mean location as an estimate of error.

2.2. Data processing and feature extraction

To examine the influence of GPS fix rate on behavioral classification, we subsampled 1 Hz GPS fixes to 10, 30, 60, 90, 120, 180, 240, 300, 600, and 900 s intervals. We calculated step lengths and turn angles of subsampled tracks via the *adehabitatLT* R package *v.* 0.3.27 [37,38] in R v. 4.3.2 [39] and used step lengths to calculate velocity (m min^{-1}). We developed a suite of seven features to describe GPS-based movement

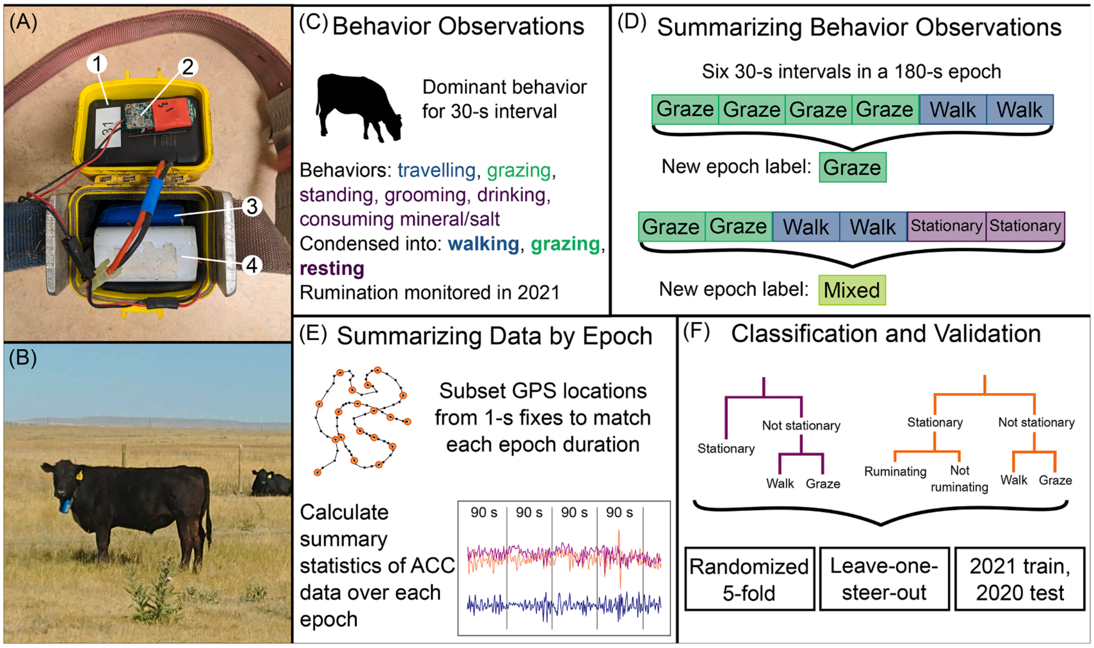

Fig. 1. Custom-built tracking devices for steer (A), containing a GPS unit (1), accelerometer (2), and batteries for both (3 and 4), which were fitted to steer via neck collars (B). We conducted visual observations of steer behavior at 30-s intervals to label GPS and accelerometer data (C) and combined 30-s into longer epochs (D). We filtered GPS data and calculated summary statistics for raw accelerometer data to generate features for each epoch (E). Finally, we used a random forest model to classify behavior, and used three cross-validation methods to assess performance (D).

including turning angle, incoming velocity (i.e., the velocity of movement from the previous point to the current location) and outgoing velocity (i.e., the velocity of movement from the current location to the next location), moving window average and standard deviation of turning angles over five locations (to get at measures of tortuosity), and count and sum of points within a 10 m radius (measures of point proximity; Table 1; [36]). We included both incoming and outgoing velocity, with the expectation that differences between the two would improve the model's ability to differentiate behavior, and perhaps select the more erratic movements as stationary (i.e., because of error). We generated buffers (i.e., circles of 10-m radii around locations) using the *sf* R package *v.* 1.0–14 [40].

To examine the influence of summarizing 12 Hz accelerometer data across various epochs on behavioral classification, we first partitioned the raw acceleration signal of each axis into static and dynamic components to separate out the effects of gravity from motion [41]. We used an approximately 3-s moving window (38 data points to account for slight variation above 12 Hz) to estimate static acceleration [42] and subtracted the static acceleration (denoted as S_X, S_Y, S_Z) from the raw acceleration to obtain acceleration from dynamic movement alone (D_X, D_Y, D_Z; [41]). Like the GPS data, we summarized acceleration data over 10, 30, 60, 90, 120, 180, 240, 300, 600, and 900 s epochs, calculating a suite of features to describe animal movement, including the vectorial sum of dynamic acceleration (VeDBA; [43]), pitch [44], and means, standard error, skew, kurtosis, minimum, and maximum of each axis, along with pitch and VeDBA, resulting in a total of 48 features (Table 1). We reiterate that an epoch in this study refers to a time interval over which we have aggregated raw data [24,25], though they have an alternative definition for neural networks [45]. We centered and scaled all variables and used recursive feature elimination to reduce the number of predictors for the accelerometer data [46] via the *caret* package v. 6.0–94 [47] for each epoch. This removed eight features that were determined to be the least influential across all 10 epochs (mean D_X, minimum D_X, maximum D_X, mean D_Y, mean D_Z, maximum VeDBA, D_X skew, and S_X skew).

2.3. Behavior observations

To translate GPS and acceleration signals into behavior metrics, in-field observations of collared steers were conducted periodically during the two grazing seasons. Six or 8 observers were trained as a group to record cattle behavior in 2020 and 2021, respectively. One observer followed and recorded the behaviors of a single steer, while up to 8 observers may have been observing different steers concurrently (in the same or a different pasture). Observations began during morning hours and continued until early afternoon (typically ranging 5–6 h), to encompass bouts of various behaviors within a given day. Observers used a smartphone app (Emerald Time; Emerald Sequoia LLC) to synchronize their observations with satellite time. Activity classes consisted of travelling (walking without grazing and head up), grazing (including grazing while walking if the animal's head was down and it harvested forage), standing, bedding (lying down), grooming, drinking, or consuming mineral/salt (Fig. 1), based on behavior descriptions by Kilgour et al. [48]. Observers used the same methods described by Ganskopp and Bohnert [49], as modified by Augustine and Derner [50], to use 30-s intervals instead of 1-min intervals during the observation period. Within each 30-s intervals, observers recorded the behavior that was performed for the majority of the interval. In 2021, we additionally recorded whether steers were ruminating (i.e., chewing rumen bolus material) when they were bedding or standing. Because we obtained relatively low sample sizes of walking, we retroactively supplemented visual observations of walking with data collected during steer pasture rotations in 2021. These rotations were periods when steers were "known" to be walking, so we considered them to be analogous to visual observations.

We conducted two separate classification schemes, one which aimed only to identify three categories for classification: stationary (including standing, bedding, grooming, drinking, and consuming mineral/salt), grazing, and walking (similar to previous studies of cattle behavior [19, 51]), and another that aimed to identify our three categories with the stationary category split into ruminating or not ruminating. To assess behavior over different epochs, we summarized the 30-s observations by considering how many of the 30-s intervals within the longer epoch (e.

Table 1

Features derived from GPS locations (7) and accelerometer (ACC; 48) data for predicting free-ranging cattle behavior. The final column indicates which of the five device combinations in which each feature was included. Classification schemes including both devices therefore had 55 features before application of recursive feature elimination. Based on the results of the recursive feature elimination method, we removed mean D_X, minimum D_X, maximum D_X, mean D_Y, mean D_Z, maximum VeDBA, D_X skew, and S_X skew from all models incorporating ACC data.

Feature	Description	Device combination(s)
GPS		
Turn angle	Relative angle of movement path.	GPS+ACC, GPS-only, GPS+VeDBA, GPS+Pitch
Outgoing velocity	Step length/time from previous point to focal point (m/min)	GPS+ACC, GPS-only, GPS+VeDBA, GPS+Pitch
Incoming velocity	Step length/time from focal point to next point	GPS+ACC, GPS-only, GPS+VeDBA, GPS+Pitch
Buffer Point Count[1]	Count of points over a 21-point moving window (10 before and 10 after focal point) that are included in a 10 m buffer of the focal point	GPS+ACC, GPS-only, GPS+VeDBA, GPS+Pitch
Buffer Point Sum[1]	Sum of point counts within a 10-m buffer around each point in a 21-point window	GPS+ACC, GPS-only, GPS+VeDBA, GPS+Pitch
|Rolling mean angle|	Absolute value of moving window average of turn angles, over 5 locations	GPS+ACC, GPS-only, GPS+VeDBA, GPS+Pitch
Std. Dev. Angle	Moving window standard deviation of turn angles over 5 locations	GPS+ACC, GPS-only, GPS+VeDBA, GPS+Pitch
Accelerometer - calculated means, standard error, skew, kurtosis, minimum, and maximum of each of the following metrics:		
Static Acceleration (S_X, S_Y, S_Z)	3 s moving window average of raw accelerometer data; represents acceleration due to gravity	GPS+ACC, ACC-only
Dynamic Acceleration (D_X, D_Y, D_Z)	Calculated as the difference between raw acceleration and static acceleration; represents acceleration due to movement	GPS+ACC, ACC-only
VeDBA	Vectorial sum of dynamic body acceleration, calculated as: $\sqrt{D_X^2 + D_Y^2 + D_Z^2}$	GPS+ACC, GPS+VeDBA, ACC-only
Pitch	Angle of head, derived from static acceleration calculated as: $arctan\left(\frac{S_X}{\sqrt{S_Y^2 + S_Z^2}}\right)$	GPS+ACC, GPS+Pitch, ACC-only

[1] See Brennan et al. (2021) for detailed description.

g., the 180-s epoch was comprised of 6 30-s observation intervals; Fig. 1) were classified as a single behavior, and assigned the behavior that encompassed the majority (i.e., $\geq 50\%$) as the label for the longer epoch. If all behaviors were $< 50\%$ of the epoch, we created a new behavior class we labeled as 'mixed.' For the 60 s epoch, we assigned the behavior as grazing if at least one of the two in-field observations was listed as grazing, and if neither was grazing, we prioritized walking.

Because there were many more observations of stationary behavior than grazing, walking, and mixed behaviors (Table 2), before modeling we balanced the number of observations in each class [52] using a multiclass version of the synthetic majority oversampling technique that incorporates an additional cluster-based under-sampling for the majority classes [53]; this was implemented via the *scutr* R package *v.* 0.2.0 [54]. The under- and over-sampling technique resulted in each behavior class having the same number of observations, equal to the average number of observations across all classes (Table 2). Ensuring a balanced training set before attempting to classify and predict can prevent bias [55], such as inflated model accuracies [56,57]. Additionally, similar forms of data augmentation have proven useful for increasing performance of deep learning methods applied to animal behavior classification from accelerometers [58]; therefore, we expected that the under- and over-sampling would assist in preventing our models from overfitting.

2.4. Classification and model validation

For each classification scheme (one without rumination and one with), and epoch (10, 30, 60, 90, 120, 180, 240, 300, 600, and 900 s), we developed classifiers using GPS units and accelerometers (ACC) individually, as well as both devices combined (GPS+ACC). Additionally, we examined the implications of a simplified GPS+ACC dataset, by combining GPS with mean pitch (GPS+Pitch) or mean VeDBA (GPS+VeDBA), excluding the remaining features calculated from the accelerometer data (Table 1). For the classification scheme with rumination, we examined classification using ACC-only data because we expected the jaw movement would not be detected by location data although jaw movements might be similar between grazing and ruminating [59]. We also examined a GPS+ACC model, anticipating that the GPS data would be useful for differentiating a stationary state from grazing. We classified behavior using random forest models [60], which have been used frequently with high accuracy (e.g., [61,62]) implemented using the *ranger* R package *v.* 0.15.1 [63]. We grew 2000 trees in our random forests and used a grid search to tune random forest models to determine values for the number of features considered at splits, minimum number of nodes in each tree, sampling scheme, and the splitting rule [64,65]. We tested 2–4 values for each hyperparameter, based on recommendations of Boehmke and Greenwell [64], and assessed performance by area under the curve. Tuned hyperparameter values varied across devices and epochs and are shown in Supplementary Materials Appendix B (Table B1 and Table B2).

For each of our models, we performed multiple cross-validations to summarize overall performance. We first conducted a randomized 5-fold cross validation (using an 80/20 split), and then held out individual steer as the validation data [66], both techniques of which are frequently used in the literature, but the leave-one-steer-out method was expected to be more representative of the performance of the algorithm on unobserved cattle [67]. We grouped 'individuals' by deployment because collars were refit between deployments and may have been fitted to a new individual, which we expected might result in variation in accelerometer measurements due to differences in collar fit or individual-specific movements. Finally, we trained our random forest model on 2021 data (n = 45 steers) and used the 2020 observation data (n = 15 steers) as a validation set to assess potential generalizability of our model onto unseen individuals under somewhat different forage conditions (i.e., precipitation was below average in 2020 resulting in much less vegetation growth than was seen in 2021). We grew separate random forests for predicting on test data and for assessing feature importance (using the same seed values), as suggested by Nembrini et al. [68]. We then assessed feature importance via the corrected impurity index [68], which was normalized to be between 0 and 1 for relative comparison across epochs and devices. Confusion matrices for all cross validations are provided in the supplementary materials.

Table 2

Number of behavior observations of each behavior at each epoch across device combinations and behavioral classification schemes. The rows for balanced classes indicates the number of observations of each behavior after over- and under-sampling. For five-fold cross-validation, we used an 80/20 split to partition all of the observations into training and testing sets.

	Epoch									
	10	30	60	90	120	180	240	300	600	900
No Ruminating										
GPS-only										
Walking	2943	2943	1453	917	599	369	277	208	92	42
Grazing	5874	5874	3112	1941	1394	935	696	555	269	163
Stationary	11,047	11,047	5174	3608	2594	1715	1268	1020	468	295
Mixed	-	-	138	45	267	170	117	103	53	49
Balanced Classes	6621	6621	2469	1628	1214	797	590	472	220	137
ACC-only										
Walking	8754	8754	4129	734	501	319	235	182	88	53
Grazing	4823	4823	2529	1601	1173	795	591	481	243	159
Stationary	2341	2341	4129	2864	2093	1405	1050	849	420	276
Mixed	-	-	97	27	189	127	95	83	88	50
Balanced Classes	5306	5306	1979	1306	989	662	493	399	199	134
GPS+ACC										
Walking	2122	2122	1054	667	445	273	199	157	72	32
Grazing	4151	4151	2179	1374	1002	677	502	403	199	126
Stationary	7852	7852	3706	2570	1858	1238	911	734	342	219
Mixed	-	-	86	25	167	104	76	67	35	34
Balanced Classes	4708	4708	1756	1159	868	573	422	340	162	103
GPS+Pitch										
Walking	2122	2122	1054	667	445	273	199	157	72	32
Grazing	4151	4151	2179	1374	1002	677	502	403	199	126
Stationary	7852	7852	3706	2570	1858	1238	911	734	342	219
Mixed	-	-	86	25	167	104	76	67	35	34
Balanced Classes	4708	4708	1756	1159	868	573	422	340	162	103
GPS+VeDBA										
Walking	2122	2122	1054	667	445	273	199	157	72	32
Grazing	4151	4151	2179	1374	1002	677	502	403	199	126
Stationary	7852	7852	3706	2570	1858	1238	911	734	342	219
Mixed	-	-	86	25	167	104	76	67	35	34
Balanced Classes	4708	4708	1756	1159	868	573	422	340	162	103
With Ruminating										
ACC-only										
Walking	2341	2341	1162	734	501	319	235	182	88	53
Grazing	4823	4823	2529	1601	1173	795	591	481	243	159
Stationary	4408	4408	2053	1442	1051	710	528	418	201	134
Ruminating	3688	3688	1819	1211	912	609	456	368	180	119
Mixed	-	-	97	27	189	127	95	83	46	50
Balanced Classes	3815	3815	1532	1003	765	512	381	306	152	103
GPS+ACC										
Walking	2122	2122	1054	667	445	273	199	157	72	32
Grazing	4151	4151	2179	1374	1002	677	502	403	199	126
Stationary	3939	3939	1835	1288	928	624	455	359	162	104
Ruminating	3338	3338	1647	1095	821	542	401	326	153	97
Mixed	-	-	86	25	167	104	76	67	35	34
Balanced Classes	3388	3388	1360	890	673	444	327	262	124	79

Metrics to assess model accuracy are derived from the number of true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN). For each cross-validation, we calculated classification accuracy as the ratio of TP + TN compared to the total number of observations (i.e., as a metric of how many observations were correctly classified), averaging the values for 5-fold and leave-one-steer-out cross validations to present the average expected performance. We then examined behavior-specific sensitivity, specificity, and true skill statistic. Behavior-specific metrics essentially consider the classification as a binary problem where the behavior of interest is the positive case, while the remaining behaviors make up the negative cases [69]. Sensitivity, defined as $TP/(TP+FN)$, is the true positive rate and indicative of the proportions of observations that are identified as that behavior, while specificity, $TN/(TN+FP)$, is the true negative rate and a measure of how well the model identifies observations that are not the behavior of interest [70]. Using sensitivity and specificity, we calculated the true skill statistic (TSS; $TSS = sensitivity + specificity - 1$) for each behavior category. TSS values can range from 1 to −1, with a value of 1 indicating perfect agreement and values ≤ 0 being equivalent to random predictions. Because grazing and rumination were our main behaviors of interest, we plotted sensitivity against specificity to visualize how well models identified observations that were or were not grazing or rumination. Performance measures were estimated using the *caret* (*v.* 6.0–94; [47]) and *pROC* (*v.* 1.18.5; [71]) R packages.

2.5. Activity budgets and travel distance from classified behavior

Having used the 2021 training data to create models, we then classified all unlabeled 2021 data across various device combinations and epochs for both the classification scheme without rumination (GPS, ACC, GPS+ACC, GPS+Pitch, and GPS+VeDBA) and the classification scheme including ruminations (ACC and GPS+ACC). For each scenario, we then summarized the time each steer spent grazing and ruminating per day, assuming that steers performed the behavior for the entirety of any epoch classified as grazing or ruminating. At each epoch, we also assessed daily travel distances using all the data, then removed observations classified as stationary behavior, and recalculated daily travel distances using only data predicted to be walking or grazing. In our assessment of classified data, we included only full days with >98% of expected collected data.

3. Results

In 2020 we obtained 3929 observations of steer behavior at a 30-sec resolution that were matched to GPS data (~33 h, 8 steers), 2470 observations that were matched to ACC data (~21 h, 8 steers), and 869 observations that matched both ACC and GPS data (~7 h, 5 steers). In 2021, we obtained 20,858 observations of steer behavior that was matched to GPS data (~187 h, 44 steers), 15,918 observations of ACC data (~133 h, 32 steers), and 14,805 observations matched to both ACC and GPS data (~123 h, 30 steers). We classified data across 57 steers in 2021 (15–125 full days per steer) for GPS alone, 54 steers (13–130 days) for ACC alone, and 52 steers (8–88 days) for GPS+ACC, GPS+Pitch, and GPS+VedBA, resulting in approximately 3080 cattle days classified across the entire grazing season, using training data from 2021. We assessed location error from ~5.2 million GPS fixes across 11 dropped collars. Mean error of stationary locations (based on the mean location) was 2.78 m ($\sigma = 1.76$ m) and ranged 0.10–14.5 m.

3.1. Model performance

3.1.1. Behavioral scheme without rumination

Based on a randomized 5-fold cross validations, ACC and GPS+ACC had the greatest classification accuracy for stationary, grazing, and walking behaviors, while GPS alone often had the lowest classification accuracy (Table 3, Fig. 2A). Despite a substantial decrease in size of the training dataset (e.g., the number of observations of each behavior category in the GPS+ACC model decreased from 4708 to 103), classification accuracy remained above 0.90 for ACC and GPS+ACC across epochs (Table 3, Fig. 2A). For all device combinations, variation in classification accuracy was lowest between 10 and 30 s and greatest between 600 and 900 s (Fig. 2A). Amongst all behaviors, TSS scores were generally the greatest for ACC or GPS+ACC, although the epoch with the greatest TSS score varied by behavior (Fig. 2B). Grazing TSS values ranged from 0.66 for GPS-only to 0.94 for GPS+ACC, with the greatest TSS at 600 s (Fig. 2B). Grazing sensitivity (range of 0.73–0.96) and specificity (range of 0.90–0.99) were both greatest for GPS+ACC, followed closely by ACC and GPS+VeDBA, while GPS+Pitch and GPS alone had the lowest sensitivities (Fig. 2C). Sensitivity was greatest at 600 s while specificity exceeded 0.98 for most epochs ≥ 60 s in models of GPS+ACC and ACC alone.

Leave-one-steer-out cross validation showed similar trends to the randomized 5-fold cross validation, with GPS+ACC having the greatest classification accuracies (Table 3, Fig. 2A). TSS was lower and more variable for all behaviors across devices for leave-one-steer-out cross validation than for the randomized 5-fold cross validation (Fig. 2B). Grazing TSS was greatest for GPS+ACC at 600 s (0.90) and at 900 s (0.84). The greatest sensitivity values were again obtained by a GPS+ACC device combination, with select epochs of ACC and GPS+VeDBA also performing well (Fig. 2C). GPS+ACC at epochs ≥600 s had the greatest sensitivity (≥0.90), and epochs ≥ 300 s also performed well for ACC and GPS+VeDBA (Fig. 2C). Specificity was greatest for GPS+ACC (0.97 at 600 s), and again ACC and GPS+VeDBA also performed well in terms of specificity, especially at epochs ≥ 60 s (>0.91; Fig. 2C).

Finally, using 2020 as a validation set, GPS+ACC consistently had the greatest classification accuracy below 300 s, and GPS+VeDBA had the greatest classification accuracy at 300 s and above (Table 3, Fig. 2A). Grazing TSS was greatest in GPS+VeDBA at 900 s (0.91), followed closely by GPS+ACC at 90 s (0.90; Fig. 2B). Sensitivity for grazing ranged 0.41–1.0 and was generally greatest for GPS+VeDBA, followed closely by GPS+ACC for epochs 90, 900, and 240 s (Fig. 2C). We note greater variability in specificity for validating on 2020 data (0.62–0.97), and while GPS+Pitch had the overall greatest specificity, the majority of the best-performing models were again GPS+ACC, ACC alone, or GPS+VeDBA (Fig. 2C). Specificity was greatest for longer epochs than for 10 or 30 s epochs (Fig. 2C).

3.1.2. Behavioral scheme with rumination

When we partitioned stationary behavior into ruminating and not ruminating, 5-fold cross validation indicated similar classification accuracies between ACC-only and GPS+ACC across all epochs (Table 4, Fig. 3A). TSS for ruminating while stationary was maximized at 0.75 at 240 s with GPS+ACC and 0.90 at 300 s with ACC alone. In contrast, TSS for grazing was relatively stable across most epochs and device combinations (falling between 0.89–0.92 between 30 and 120 s; Fig. 3B). Sensitivity and specificity values for grazing were nearly exclusively greater for GPS+ACC than for ACC alone across most epochs (Fig. 3C). Sensitivity for ruminating while stationary was above 0.90 for ACC only at various epochs (60, 90, 180, and 300 s), and while specificity was greatest for ACC only at 300 s (0.98), GPS+ACC also exceeded 0.97 at 30–90 s (Fig. 3C).

In the leave-one-steer-out cross validation, GPS+ACC and the ACC-only model also showed similar classification accuracies across all epochs, again with an increased amount of variability compared to 5-fold cross validation and as the epoch increased in size (Table 4, Fig. 3A). The greatest TSS for ruminating was achieved at 300 s using GPS+ACC (0.71; Fig 3B). For grazing TSS, GPS+ACC had better scores than ACC alone, with the greatest values at 600 s. Sensitivity and specificity for grazing was generally greater with GPS+ACC, although specificity was generally higher than sensitivity, with both metrics exceeding 0.90 only at 600 and 900 s (Fig. 3C). Ruminating while stationary showed a similar pattern of specificity exceeding sensitivity, with the greatest in both metrics being achieved using ACC only (Fig. 3C). We note that rumination behavior was not recorded by observers in 2020, so we could not use 2020 as validation data.

3.2. Feature importance

For the behavioral scheme without rumination, we observed similarities in features driving classifications across devices and epochs (Fig. 4A). For instance, mean VeDBA was one of the top five features in every device combination in which it was included, as were outgoing and incoming velocities, standard error of the D_Z axis (i.e., motion of the head up and down), and the buffer point sum variable (a measure of stationarity; Fig. 4A). The relative decrease in impurity was lower for the top five features of GPS+ACC and ACC alone than for other device combinations, indicating that single features were not driving classification (Fig. 4A). For the behavioral scheme with rumination, the GPS+ACC device combination showed incoming and outgoing velocity as frequently in the top five most important features, in addition to minimum and mean VeDBA and standard error of the D_Z axis which was similar to the important variables seen in our other classification scheme

Table 3
Device combination with greatest classification accuracy of stationary, mixed, grazing, and walking behaviors in free-ranging cattle in the shortgrass steppe of northeastern Colorado across epochs estimated from three methods of validation (randomized 5-fold, leave-one-steer-out, and predicting on 2020 data). The associated average classification accuracies are shown in parentheses.

Epoch (s)	Random 5-fold	Leave-one-steer-out	2020 Validation
10	GPS+ACC (0.92)	GPS+ACC (0.87)	GPS+ACC (0.86)
30	GPS+ACC (0.94)	GPS+ACC (0.89)	GPS+ACC (0.89)
60	GPS+ACC (0.94)	GPS+ACC (0.86)	GPS+ACC (0.88)
90	GPS+ACC (0.95)	GPS+ACC (0.90)	GPS+ACC (0.91) GPS+VeDBA (0.91)
120	ACC (0.93)	GPS+ACC (0.85)	GPS+ACC (0.85)
180	GPS+ACC (0.95)	GPS+ACC (0.84)	GPS+ACC (0.87)
240	GPS+ACC (0.94)	GPS+ACC (0.84)	GPS+ACC (0.86)
300	GPS+ACC (0.96)	GPS+ACC (0.82)	GPS+VeDBA (0.88)
600	ACC (0.96)	GPS+ACC (0.89)	GPS+VeDBA (0.90)
900	GPS+ACC (0.94)	GPS+ACC (0.82)	GPS+VeDBA (0.91)

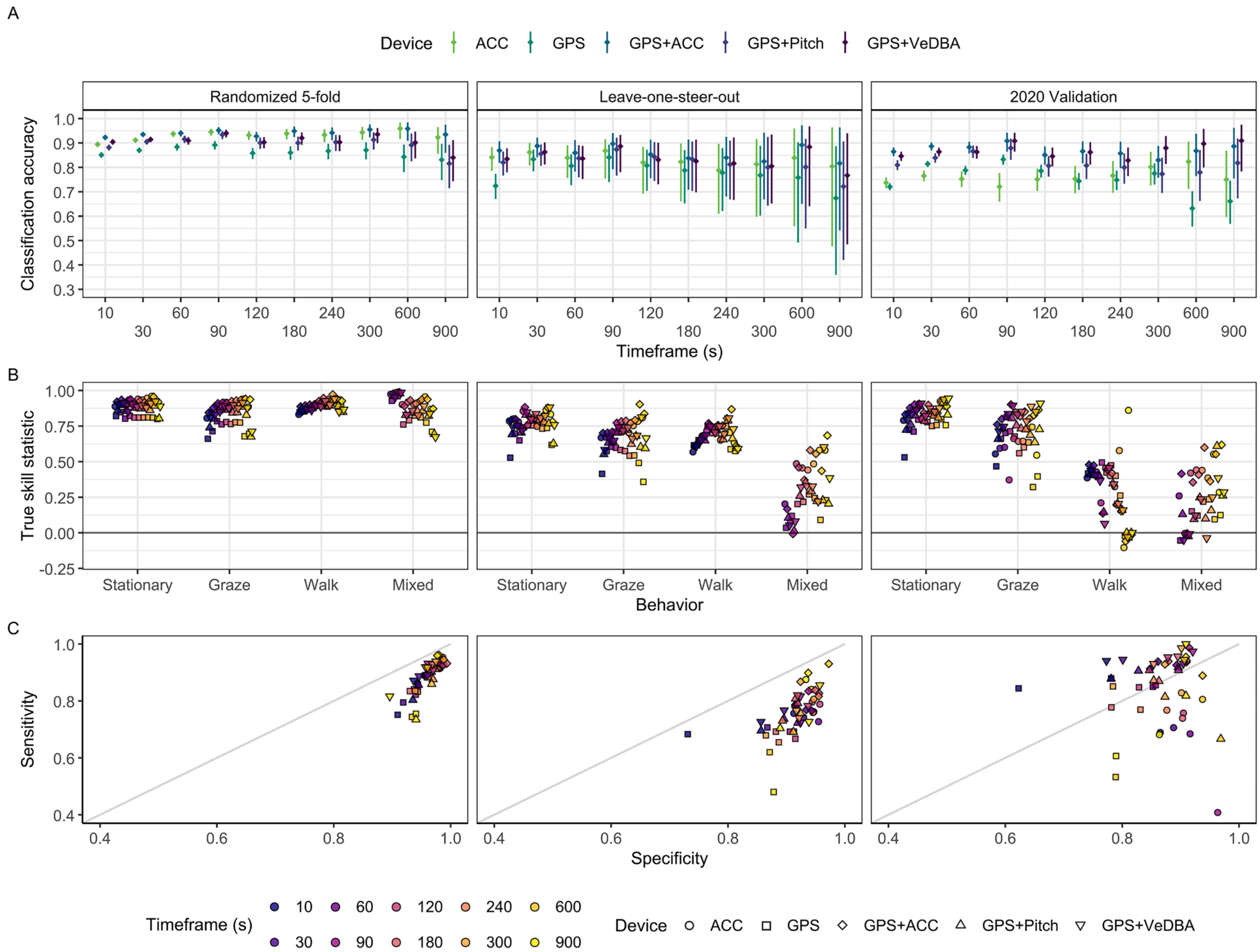

Fig. 2. Performance metrics for random forest models classifying free-ranging steer behavior as stationary, mixed (≥ 60 s), grazing, and walking in 2021 in shortgrass steppe of Colorado, USA. We summarized (A) classification accuracy (with 95% confidence intervals), (B) the true skill statistic for each behavior, and (C) sensitivity against specificity for grazing. We compared metrics across different methods of cross validation, including randomized 5-fold cross validation (left column), leaving an individual steer out (center column), and finally trained the models on data from 2021 and used data from 2020 as a validation data set (right column).

Table 4
Device combination with greatest average classification accuracy of stationary, ruminating while stationary, mixed, grazing, and walking behaviors in free-ranging cattle in the shortgrass steppe of northeastern Colorado, across epochs estimated from two methods of validation (randomized 5-fold and leave-one-steer-out). The associated average classification accuracies are shown in parentheses.

Epoch (s)	Random 5-fold	Leave-one-steer-out
10	GPS+ACC (0.87)	GPS+ACC (0.77)
30	GPS+ACC (0.90)	GPS+ACC (0.80)
60	GPS+ACC (0.90)	GPS+ACC (0.79)
90	ACC (0.91)	GPS+ACC (0.82)
120	ACC (0.89)	GPS+ACC (0.78)
180	ACC (0.90)	GPS+ACC (0.78)
240	ACC (0.87)	GPS+ACC (0.78)
300	ACC (0.90)	GPS+ACC (0.74)
600	GPS+ACC (0.89)	GPS+ACC (0.78)
900	GPS+ACC (0.89)	GPS+ACC (0.72)

(Fig. 4). In the ACC-only classifications, minimum and mean VeDBA along with standard error of the D_X, D_Y, and D_Z axes were consistently important across epochs (Fig. 4B).

3.3. Activity budgets and travel distance

For the behavioral scheme without rumination, across epochs and device combinations, daily travel distances (from only grazing and walking) ranged on average from 3.5–7.7 km day^{-1} (Fig. 5A). Travel distances also tended to decrease as epoch increased, but in a similar manner across devices (Fig. 5A). Daily travel distances declined by an average of 1.6 km day^{-1} after removing stationary behaviors (range 1.0–2.9 km day^{-1}; Fig. 5B). Overall, we also observed minimal variation in activity budgets across devices with the exception of GPS alone, which had the shortest and longest estimates of grazing time (12.3 h day^{-1} at 10 s to 5.1 h day^{-1} at 900 s). Otherwise, estimates of grazing time ranged from 7.6–9.9 h day^{-1} on average across devices and epochs (Fig. 5C). Grazing was predicted to occur with higher frequency just after dawn and before dusk (Fig. 5D; Supplementary Materials: Fig. C1).

For the behavioral scheme with rumination, daily travel distances (excluding stationary behaviors) were estimated only from GPS+ACC and ranged on average from 4.8 to 7.6 km day^{-1} across epochs, decreasing as epoch increased (Fig. 6A). Differences between travel distances calculated with all locations instead of with the removal of stationary behavior were approximately 1 km greater. Rumination time was essentially the same when assessed with GPS+ACC (5.5–7.0 h day^{-1}) compared to only ACC (5.8–7.8 h day^{-1}; Fig. 6B). Time spent ruminating

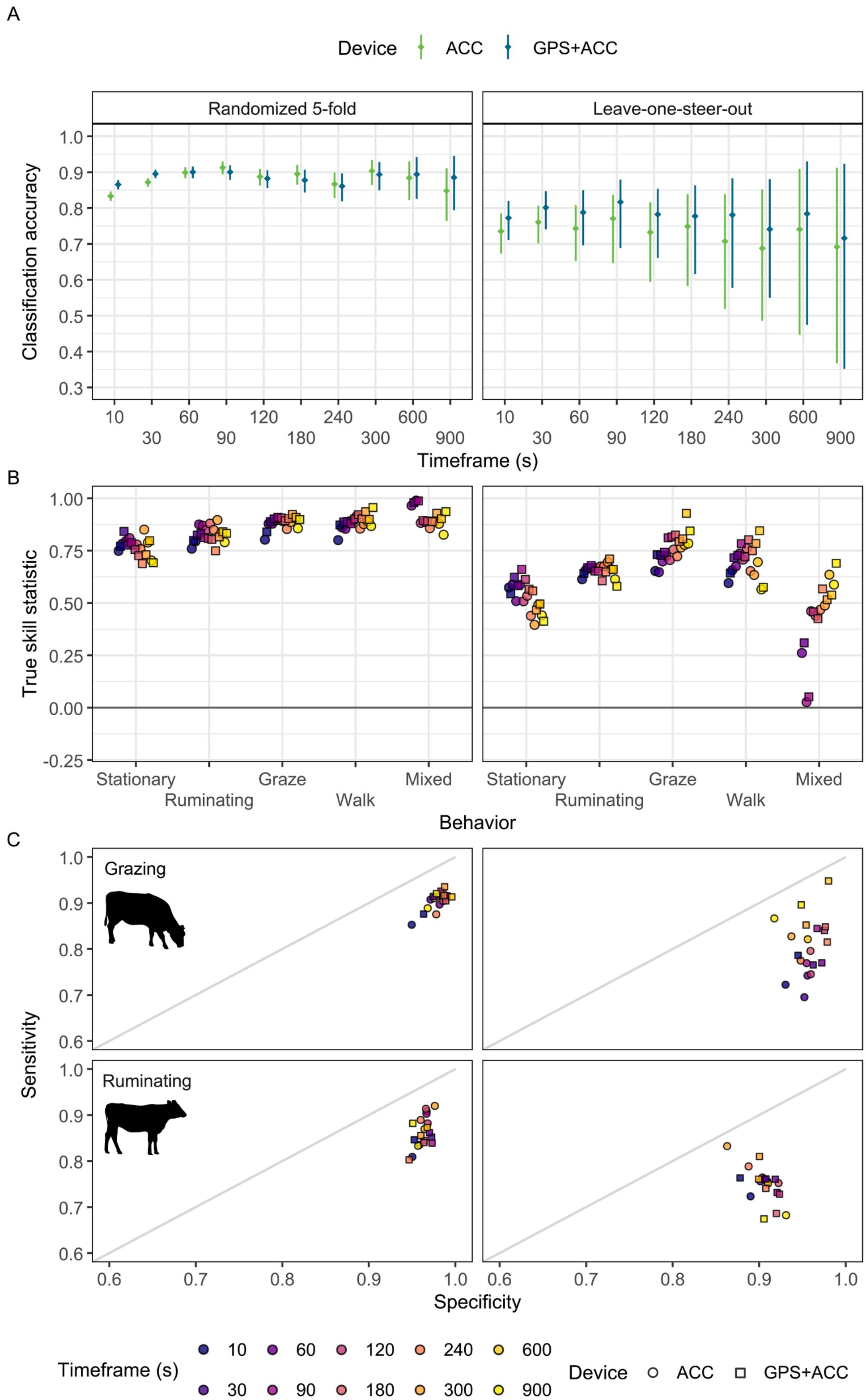

Fig. 3. Performance metrics for random forest models classifying free-ranging steer behavior as stationary and not ruminating, ruminating while stationary, mixed (≥ 60 s), grazing, and walking in 2021 in shortgrass steppe of Colorado, USA. We summarized (A) classification accuracy (with 95% confidence intervals, (B) the true skill statistic for each behavior, and (C) sensitivity against specificity for grazing and ruminating while stationary. We compared metrics across two cross validation methods: randomized 5-fold cross validation (left column) and leaving an individual steer out (right column).

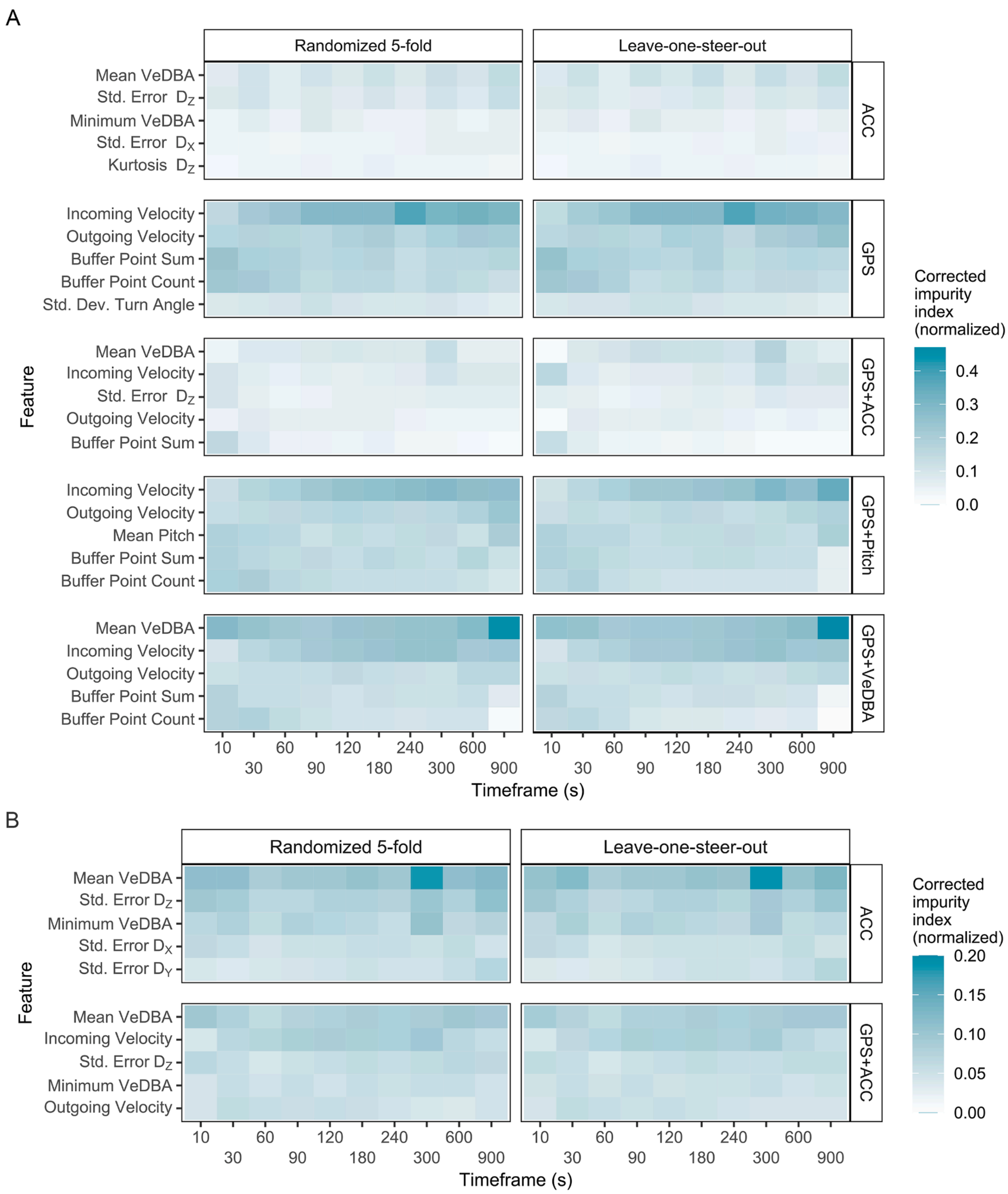

Fig. 4. Relative feature importance of the top five features across epochs (x-axis), device combinations, and cross-validation method for (A) the behavioral classification scheme not including rumination and (B) the behavioral classification scheme including rumination. Feature importance was normailized to show relative decrease in impurity. Number of features varied by device combination, with GPS+ACC having 47 features, GPS+VeDBA and GPS+Pitch having 8, ACC-only having 41, and GPS-only having 7 features.

also decreased as epoch increased (Fig. 6B). In contrast, average time being stationary while not ruminating was relatively stable across epochs (5.6–6.7 h day^{-1}) except for longer epochs whereby this behavior dropped to a minimum of 4.5 h day^{-1} at 300 s and a maximum of 7.0 h day^{-1} at 600 s (Fig. 6B). Average grazing time per day was also similar between device combinations, ranging from 7.9–8.8 h day^{-1} for GPS+ACC and 7.5–8.3 h day^{-1} for ACC alone (Fig. 6B). Grazing time was again most frequent near dawn and dusk, while peak rumination while stationary hours were overnight (Fig. 6C).

4. Discussion

Our objectives were to determine an optimal combination of devices and epochs for identifying grazing and rumination behavior in free-ranging cattle fitted with GPS and accelerometers (ACC), while striving to limit hardware and software complexity, and to assess implications for interpretation of behaviors classified at various epochs. We aimed to provide optimum ranges for data collection, as called for by Anderson et al. [31], as a means to establish a benchmark for future studies and applications. We found that the highest behavioral prediction accuracy (0.90 based on leave-one-steer-out analysis) could be achieved using GPS plus the full suite of accelerometer metrics analyzed

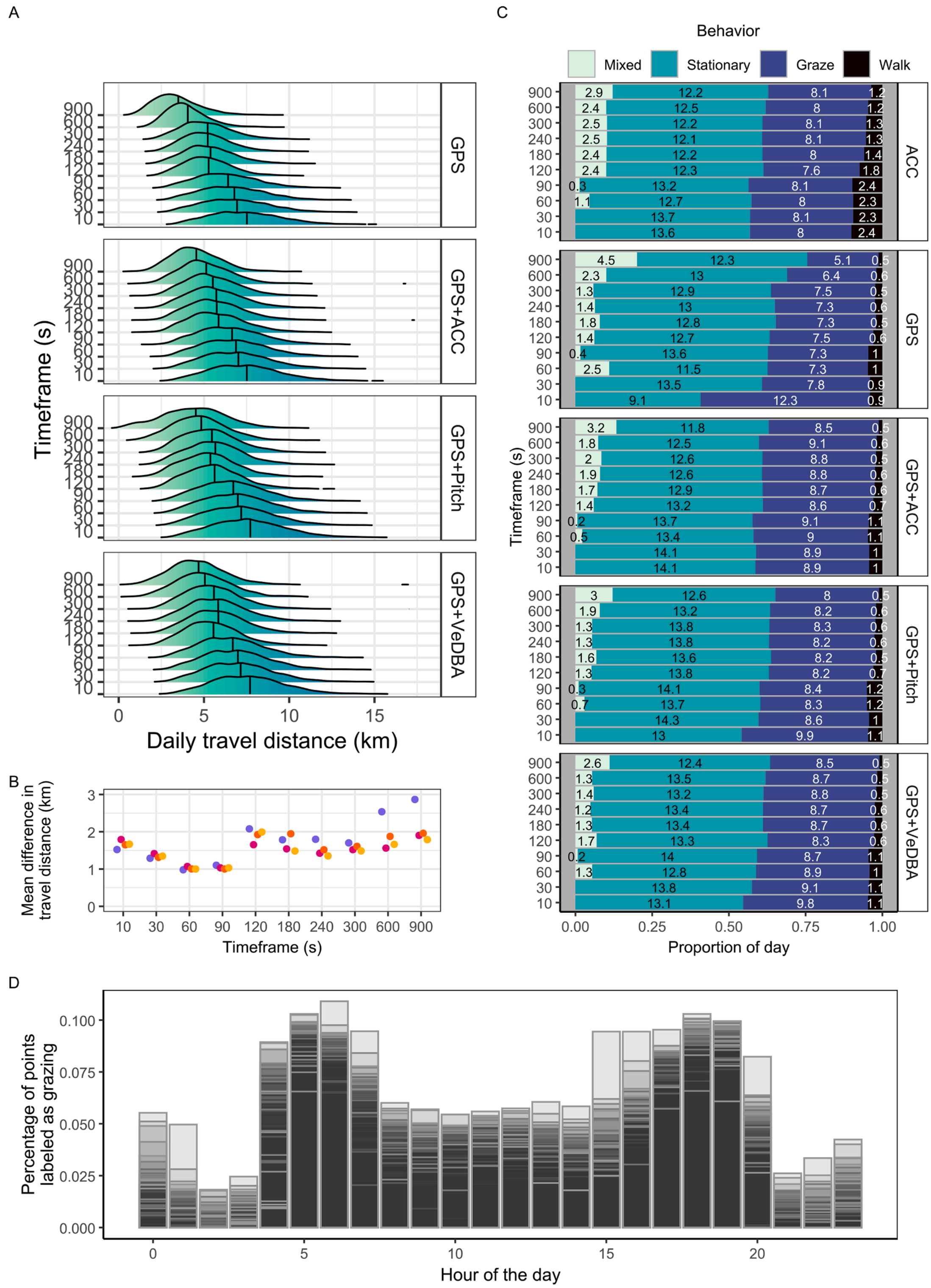

Fig. 5. Summary of cattle data classified with the behavioral classification scheme without ruminating. The distribution of daily travel distances show the summed distance between locations for classfied steer data (A), excluding stationary and mixed behaviors, and the difference in estimates between including and excluding lcoations classified as stationary or mixed are shown in panel B. Vertical lines within densities indicate the mean daily travel distance for each epoch. Activity budgets (C) of each device combination reflect mean values in hours for amount of time spent in that behavior each day across device combinations and epochs. Panel D shows the relative frequency of data points classified as grazing for each hour of the day at 90 s for GPS+ACC. Darker shading indicates more individuals, while the lightest shading has the fewest individuals.

at a 90-s epoch. However, if a computationally less intensive prediction is desired, overall accuracy only declined to 0.89 with the simplified GPS+VeDBA model at the 90-s epoch. Perhaps most importantly, we found that using the full suite of accelerometer metrics calculated at a 30-s epoch, without any GPS data, could achieve an accuracy of 0.86, with even smaller confidence intervals than the 90-s epoch predictions. When accelerometer metrics were combined with GPS fixes at 30- to 120-s epochs, prediction accuracy was only slightly above 0.86.

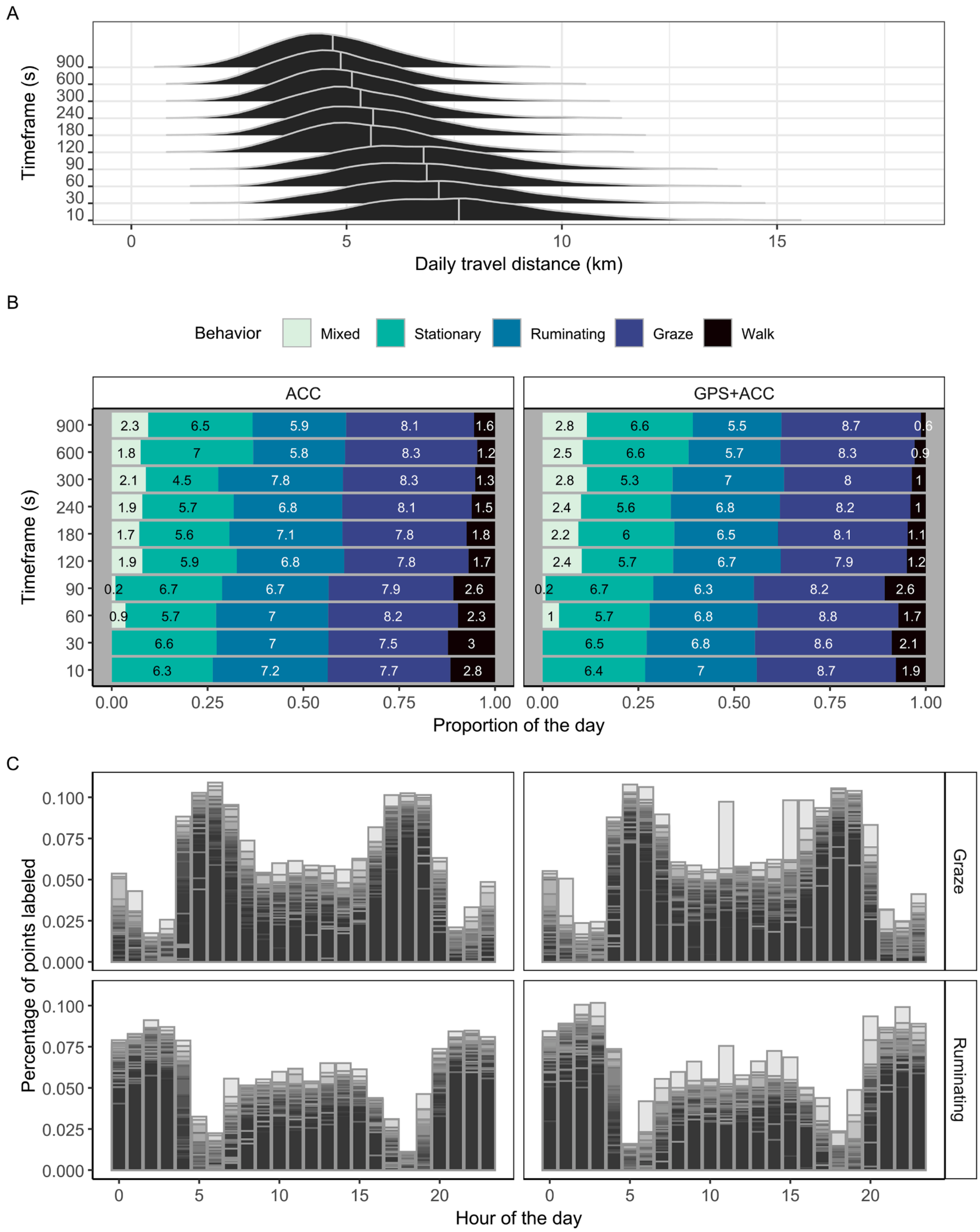

Fig. 6. Summary of cattle data classified according the behavioral classification scheme with ruminating while stationary. The distribution of daily travel distances, estimated from GPS+ACC, show the summed distance between locations for classfied steer data (A), excluding stationary and mixed behaviors. Vertical lines within densities indicate the mean daily travel distance for each epoch. Activity budgets (B) of each device combination reflect mean values in hours for amount of time spent in that behavior each day across device combinations and epochs. Panel C shows the relative frequency of data points classified as grazing or ruminating while stationary for each hour of the day at 90 s for ACC (left) and GPS+ACC (right). Darker shading indicates more individuals, while the lightest shading has the fewest individuals.

Therefore, if the priority is to minimize battery requirements by using a GPS fix rate that is longer than 2 minutes, the optimal approach is to predict behavior using the accelerometer metrics at a 30-s epoch, and then combine this with whatever GPS fix interval is desired given desired battery life and objectives for assessing the animal's location and movement pattern. For example, if GPS fixes are collected at 5-min (300 s) intervals, then the optimal approach is to predict behavior at 30-s epochs using the accelerometer metrics, and then summarize these for each 5-min interval between GPS fixes. Similarly, if the goal is to include prediction of rumination behavior, then prediction accuracy is maximized using a 90-s epoch for GPS+ACC, but only slightly lower accuracy is achieved using the accelerometer-only data at 30 s, which could again be combined a 5-min or longer GPS fix interval.

4.1. Performance across device combinations and epochs

While it is not surprising that the complexity of information obtained from GPS+ACC generally achieved the greatest accuracy across epochs, our results indicate that GPS units in combination with VeDBA can achieve similar accuracies in simplified behavioral classification schemes. This trade-off allows for less processing complexity while maintaining accurate behavioral predictions, a trade-off that could allow for easier on-board calculation [72]. Notably, VeDBA is the vectorial sum of all three axes, and therefore does not depend on orientation [43], which means this metric is robust to collar rotations or differences in orientation with unit attachment (e.g., as suggested in Versluijs et al. [69]). While ACC alone was also successful in accurately classifying behaviors, the usefulness in this context is likely limited, as we expect most ranchers and researchers in extensive rangelands would also be interested in an associated location for behavior, and the processing cost in time and complexity likely outweighs the practicality of this device alone.

Using GPS alone to classify behavior generally had the poorest performance, with the primary driver likely being location error. While our estimate of device error was <3 m on average, we expect that error was greater while collars were on animals relative to a stationary collar on the ground, as steers may be grouped together which may add interference to GPS signals. Shorter intervals between fixes usually improves location accuracy [73], though some researchers have suggested increased GPS error from shorter time periods due to autocorrelation and accumulation of error [74]. Additional processing of GPS data may also improve accuracy of locations (e.g., [23]); however, such methods are often computationally intensive, especially with frequent fixes [75]. Thus, researchers and producers will likely need additional sensors to obtain reliable estimates of grazing. A potential methodological enhancement would be to collect GPS data only when the accelerometer indicates movement to preserve battery life and reduce the amount of movement attributed to GPS error [76,77].

We had anticipated a greater decrease in accuracy as epochs increased due to summarizing behavior over longer time intervals, and while we noted an increase in variability as epochs became longer, average classification accuracy was sometimes just as great at 300 s as it was at 90 s. Indeed, TSS indicated similar behavior-specific performance across epochs for a given device combination. We surmise that because cattle are large, relatively slow-moving animals that spend the vast majority of their time performing a small number of behaviors [78], accelerometer signals were sufficiently differentiable at longer epochs. In contrast, if we had focused on rare or short-duration behaviors (e.g., headshaking; [79]), we might have seen a more profound impact of epoch on accuracy (as in Yu et al. [72]). The decreased accuracy observed in our ACC- and GPS-only models at 10 s is not surprising and indeed consistent with previous attempts of classifying cattle behavior at sub-minute intervals, likely a result of GPS error making it difficult to differentiate movement from stationary behaviors [80], or because the epoch is too short relative to the behavior [24]. In a similar study on donkey behavior, error was greatest at the 15-s epoch and decreased until the 120-s epoch [81], which is within the range of our optimal epochs for cattle behavior classification, though our results indicated greater performance at 60–90-s epochs. For some behaviors, a variable-time approach may improve classification accuracy [82,83], though this has the potential to increase processing requirements [84].

We used three methods of cross validation for our classification models to more robustly explore model performance related to similarities between training data and unlabeled data. First, our randomized 5-fold cross-validation was expected to have greater accuracy due to the large array of signals from a larger variety of animals which works to improve predictive ability [58]. Thus, performance decreases when one uses a leave-one-steer-out approach, given how variable animals can be in their daily activity patterns [85] or device variability [86]. Using data from 2020 showed how robust models could be across years given potential differences in forage conditions impacting acceleration or movement patterns. Despite this potential confound, accuracies were generally on par with the first two cross validation exercises, with minimal decrease in performance of grazing, although walking was classified with substantially lower success. This could be a result of steers spending more time opportunistically foraging in poor grazing conditions, rather than distinct walking and grazing periods that might be seen in years in which forage biomass was plentiful (i.e., 2021). Indeed, when using 2020 data as a validation, walking was mislabeled as grazing nearly as often as it was correctly identified as walking, therefore, we suspect the poorer performance of the models applied to data from 2020 can be attributed to differences in grazing conditions rather than individual variability or sample size (confusion matrices provided in Supplementary Materials: Appendix D).

4.2. Feature importance and differentiation of behaviors

We observed several patterns in behavior-specific performance of our random forest models. For grazing and rumination, specificity was generally high, indicating that the incidence of false negatives was greater than false positives, therefore, our models were likely underestimating these behaviors. We conjecture that these instances of ruminating and grazing are likely being confused with 'mixed' behavior, which is inherently not a clear signal. While some researchers remove observation periods that include more than one behavior before training their machine learning models, we opted to retain them in a 'mixed' category given the nature of signal aggregation that cumulated many behaviors into a single category, and indeed Resheff et al. [87] suggested that inclusion of mixed segments can be beneficial. Additionally, the number of separate behavior observations decreased as epoch increased, which may have increased variation among observations, though classification results indicated a relatively small decrease in accuracy.

While our models distinguished rumination behavior with moderate success, it comes at the cost of needing to include the full suite of accelerometer features. Using the GPS+ACC combination, we observed some of the greatest proportions of one behavior (ruminating while stationary) being classified as another (not ruminating). For example, at the shortest epochs, not ruminating was predicted to be ruminating at nearly twice the rate, while at the longest epochs, rate of misclassification was similar between the two behaviors. Indeed, we noted greater differences in TSS of all behaviors across epochs when we included ruminating. Therefore, given the challenges and costs of accurately classifying ruminating, we suggest this only be done when there is a specific interest in rumination time.

Mean VeDBA and the incoming velocity were generally the most influential variables. We were somewhat surprised that pitch was relatively less important, given that head movements were expected to help distinguish foraging behavior [50]. We had also anticipated greater importance of the turn angle between GPS locations, singly or over several time points, as we had expected extreme angles may have been indicative of stationary error [88]. The buffer point sum and count variables derived following Brennan et al. [36] were also in the top five most important variables in device combinations with GPS. Brennan et al. [36] suggested that the buffer point sum variable would likely capture locations that were scattered across a relatively small area due to GPS error when the animals were stationary, and we suspect it functioned the same way herein. However, we suggest that this variable may be refined across time intervals (i.e., adjusting the buffer radius or number of points considered), which may improve identification of stationary behaviors at the shortest time intervals.

4.3. Inferences of travel distance and activity budgets from classified data

The average daily travel distance estimated using only walking and grazing locations was 1 km shorter than the daily travel distances that included locations classified as stationary, indicating that GPS error can have a significant impact on estimates of travel distance [89]. Though our estimates of travel distance nearly doubled between the shortest and longest epochs, they were similar to those published elsewhere at both short (60 s) and long (600 s) epochs [21]. However, our estimates

(6.9–7.1 km day-1 at 5-min resolution after removing stationary locations) were less than estimates of McIntosh et al. ([30]; 9.3 km day^{-1} without removing stationary locations), which might highlight the potential impact of GPS error on estimates of daily travel distances if behavioral states are not classified. We also note variation in estimated daily travel distance may be partially due to differences in pasture [21] or herd size [33] influencing path tortuosity and velocity while grazing, in addition to effects of GPS fix rate. For example, McIntosh et al. [90] noted a strong relationship between daily travel distance and pasture size, with cattle moving 8–10 km day^{-1} in 1000–3500 ha pastures; thus, because our pastures were considerably smaller (e.g., 130–360 ha), the lower estimates of daily travel distance should perhaps be expected. When making comparisons, we also expect that breed, terrain, and water locations may also play a role in dictating how cattle move and forage [91]. Similarly, daily grazing time estimates were consistent with those generated by others (e.g., [30,36]), but they were slightly less than the 9–10 h day^{-1} predicted by Augustine et al. [33] for steers at the same study site. This difference is consistent with behavior-specific model performance metrics in our current study indicating that grazing was likely to be underestimated. Despite this, classified periods of ruminating while stationary throughout the day occurred primarily opposite of peak grazing periods, and was greater overnight than during daylight hours, which is consistent with previous observations of cattle activity budgets [48,78]. Thus, collectively it seems that our classification models produced reasonable estimates of behavior for free-ranging cattle.

4.4. *Tradeoffs between longevity and durability*

Our rate of successful data collection highlights some of the challenges of precision livestock management applications in extensive rangelands. Frequently, data loss was the result of one sensor working while the other failed (e.g., due to battery connection failure), the collar being pulled over the steers' head, or the resin case breaking open. During our study, cattle were frequently observed knocking collars against fences and water troughs, which we assume was the primary driver of device failure. Yet, commercially built tracking devices can also suffer catastrophic technical failures, averaging approximately 25% of units (but ranging up to 100%; [92]). Commercial collars generally come with a much higher price tag than custom-built devices; however, this benefit may be canceled out with the additional costs in personnel time and technical knowledge [15]. Using our custom-built devices, we were able to replace batteries and repair sensors of custom devices during periodic weighings of cattle, which is usually not an option with commercial devices. At the same time, we acknowledge that at current costs of the devices we used, applications are likely to be primarily for experimental research rather than for use in commercial operations. Further improvements in durability combined with a reduction in costs and the capacity to recharge or replace batteries may increase the effective use of these sensors in precision livestock management applications.

5. Conclusions

Our objective for this study was to guide researchers and commercial bio-logging enterprises in determining device combinations and epochs for observing behavior in free-ranging cattle. The overall information collected per day decreased exponentially as the analytical time step increased, but even summarizing data over 90-s epochs resulted in 960 epochs day^{-1}, which can still present computational challenges when collecting data over extended periods of time (i.e., a 4-month grazing season or longer). Notably, accuracy could remain high if further reduced to a 5-min (300 s) epoch (288 epochs day^{-1}). Additionally, the use of GPS+VeDBA provided accurate and reasonable classification of stationary, grazing, and walking behavior in free-ranging cattle while also reducing the number of necessary variable calculations and subsequent size of the dataset. Therefore, selecting an optimal epoch and using a reduced set of sensor features improves our ability to collect, process, and transmit data that provides inferences about cattle behavior and can have immediate impacts related to food production and rangeland conservation.

Ethics statement

All research followed the Institutional Animal Care and Use Committee protocol (#CPER-4 renewal) approved 11 June 2019 by the USDA-Agricultural Research Service in Fort Collins, Colorado, USA.

CRediT authorship contribution statement

Stephanie A. Cunningham: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation. **David J. Augustine:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Justin D. Derner:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **David Smith:** Software, Resources, Investigation. **Melanie R. Boudreau:** Writing – original draft, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.atech.2024.100646.

Data availability

Data will be made available on request.

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