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Tracking and sensor-based detection of livestock water system failure: A case study simulation ☆

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ABSTRACT

Water is an important nutrient, and its continuous provision is a critical welfare issue for cattle grazing arid and semiarid rangelands. Time and labor are needed to monitor water availability, and automated monitoring systems are a costly input on expansive rangeland pastures. The objective of this study was to evaluate the potential of detecting water system failures using Global Positioning System (GPS) tracking and accelerometers, assuming the data could be monitored in real or near-real time. Water system failure was simulated in a 1 096-ha pasture in Arizona by placing metal panels around the only drinker for 4 h (0800−1200) on three occasions in 2018 and two occasions in 2019. Randomly selected cows (10 in 2018 and 23 in 2019) of the 120 cows in the pasture were tracked with GPS collars, and 7 (2018) and 10 (2019) of the tracked cows were fitted with triaxial accelerometers. Movement intensity measured by accelerometers was greater ($P = 0.03$) on the day of simulated water failure than on control days with available water. During simulated water failure, cows remained closer to water ($P = 0.01$) after approaching the drinker (< 150 m) compared with the control period the day prior. Cows typically went to the drinker, drank, and then traveled away from the drinker and rested. On simulated water-failure days, cows remained near the drinker (< 150 m from the tank) until the panels were removed and they could drink. Real-time GPS tracking with or without accelerometer data has the potential to remotely detect water system failure, which could reduce the time for managers to repair the water system and improve cattle well-being.

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Introduction

Water is the most important nutrient and the most critical livestock well-being concern on rangelands (Bailey 2016). Stockmen must check livestock daily or every few days depending on weather conditions and water drinker storage. On rangelands, checking the availability of water for livestock is time consuming and labor intensive since extensive travel on unimproved and primitive roads is required. The ability to remotely monitor water availability for livestock could potentially result in labor savings and help stockmen respond sooner to water system delivery failures. There are currently a variety of automated water monitoring systems available to ranchers; however, the cost of deploying these systems on large numbers of water tanks and pipelines is likely to be prohibitive. A key limitation of these systems is that they must be fixed to each water point to be monitored and can't be easily moved with livestock as they change pastures. But what if there was a system that didn't require significant infrastructure investment and followed the animals wherever they were pastured? One idea is to use the animal itself as an indicator of the status of water availability. Our paper explores this concept, essentially using animal behavior monitored with on-animal sensors as the mechanism by which a rancher might be alerted to water-related issues.

Rangelands across the globe tend to be expansive and rugged, which makes observing livestock and monitoring livestock well-being a difficult, time-consuming, and labor intensive task (Bailey 2016). The extensive nature of rangelands limit stockmen's ability to observe changes in livestock behavior, detect illnesses, and identify welfare issues. Much more time is spent locating livestock, observing animal behavior and health status, and treating ill animals

in rangeland production systems compared with intensive livestock production systems (Bailey 2016).

Even before the development of the Global Positioning System (GPS), researchers were monitoring livestock distribution, nutrition, behavior, and welfare (Herbel and Nelson 1966; Herbel et al. 1967; Roath and Krueger 1982). Through time, methods of tracking have become more automated and relied less on human observations (Turner et al. 2000; Bailey et al. 2018). Researchers have used a variety of technologies to remotely monitor livestock including GPS tracking (Anderson et al. 2013) pedometers (Anderson and Kothmann 1977) and accelerometers (Terrasson et al. 2016).

Similar to stockmen, researchers monitor livestock behavior to determine the animal's interactions with environment, forage and social groups, as well as gaining insights on animal health and physiologic state. Accelerometers have been used in sheep research to detect activity (McLennan et al., 2015); individual behaviors, such as laying, standing, walking, grazing, and running (Alvarenga et al. 2016); and animal welfare concerns such as lameness (Barwick et al. 2018). Sensor placement and study design can improve the efficacy of monitoring behavior and animal states (Fogarty et al., 2019).

Technological advancements such as improved battery life, stable electrical connections, and miniaturization of electrical components have facilitated use of sensors to remotely monitor animal behavior (Fogarty et al. 2020). Previously, livestock location data were usually stored on the device but development of technologies such as long-range wide area networks (LoRa WAN) and the Internet of Things (IoT) have allowed industries to develop real-time and near real-time sensor devices (Bailey et al., 2018; Sanchez-Iborra 2018; Maroto-Molina et al., 2019).

The goal of this study is to evaluate the potential of detecting water system failures using GPS tracking and accelerometers, assuming the data could be monitored in real or near-real time. This study provides baseline data and proof of concept for future development of technologies and algorithms using GPS tracking and accelerometer systems to remotely detect water system failures on rangeland.

Methods

Animals, study site, and environment

This study was conducted at the Deep Well Ranch (DWR), located 16 km north of Prescott, Arizona (112^{0}29′W, 34^{0}41′N) and encompasses 8 004 ha of gently rolling terrain that varies in elevation from 1 434 to 1 657 m. The Köppen climate classification for Prescott, Arizona is Hot-summer Mediterranean (Csa). The average annual precipitation is 450 mm with > 40% occurring during the summer monsoon season (July through September). Minimum and maximum daily temperatures during the study periods in June 2018 varied from 12°C to 14°C and 29°C to 34°C, respectively. During July 2019 study periods, minimum and maximum daily temperatures varied from 18°C to 21°C and 32°C to 36°C, respectively. Vegetation at DWR is predominantly perennial grasslands dominated by black grama (*Bouteloua eripoda* [Torr.] Torr.), dropseeds (*Sporobolous* spp.), and purple threeawn (*Aristida purpurea* Nutt.).

The study area (North Pasture) contained 1 096 ha and varied in elevation from 1 471 to 1 542 m. A herd of 120 Corriente cow-calf pairs grazed the North Pasture from late May to October during the 2 yr of the study (2018 and 2019). Cows varied in age from 2 to 15 yr, had been raised together, and had spent at minimum the previous 6 mo together. The mean body condition score was 3.43 (standard deviation 0.42, range 2.25−5.25) at the start of the experiment (May 26, 2018). In 2019, body condition score was not recorded, but the body condition of the cattle was similar. The study was conducted in accordance with the research protocol approved by the New Mexico State University Institutional Animal Care and Use Committee (IACUC, approval numbers 2018-010 & 2019-021).

Devices

Randomly selected cattle were fitted with GPS tracking collars (IgotU GT-120 or IgotU GT 600 receivers; Mobile Action Technology Inc., Taipei, Taiwan; Knight et al. 2018a) on May 26 in yr 1 (2018) and June 5 in yr 2 (2019). The IgotU GT 600 receivers recorded positions at 2-min intervals in 2018 and 2019. The IgotU GT 120 receivers recorded positions at 2-min intervals in 2018 and 10-min intervals in 2019. During 2018, 10 cows were tracked with 7 IgotU GT 600 and 3 IgotU GT 120 receivers. In 2019, 23 cows were tracked with 7 IgotU GT 600 receivers and 16 IgotU GT 120.

Seven and 10 randomly selected cattle in 2018 and 2019, respectively, that were fitted with GPS tracking collars were also fitted with a triaxial ± 16 g Axivity AX-3 accelerometer (Axivity Ltd, Newcastle, UK) attached to Y-Tex 4-star ear tag (Y-Tex Corporation, Cody, WY). The accelerometers were attached to ear tags, and the axes corresponded to *z*−front-to-back, *y*−side-to-side and *x*−vertical. The accelerometers were configured to a sample rate of 12.5 Hz and had an expected battery life of 30 d per the manufacturer. More details about placement of this type of accelerometer on ear tags are provided by Fogarty et al. (2020).

In 2018 three IgotU600 receivers powered off before trial dates and one IgotU600 had large error in location fixes, and their data were removed from the study. In 2019, one IgotU600 receiver was lost, two IgotU600 receivers had large error in location fixes, and two IgotU600 receivers had battery failure. In 2019, six accelerometer housings broke, resulting in loss of the devices. The data from these GPS tracking collars and accelerometers were not used in the analyses. In total, 6 GPS tracking collars were used in analyses for 2018, and for 2019 a total of 16 tracking collars were used for analyses. A total of seven and six accelerometers from trials in 2018 and 2019, respectively, were used in the analyses.

Experimental design

A total of five trials were conducted. Three trials were conducted in 2018 (June 6, 12, and 18), and two trials were conducted 2019 (July 17 and 19). During these dates (trials), animal access to water was restricted for 4 h (0800−1200 h) using metal livestock panels (2.1 × 1.5 m) placed next to the 1 900-L water tank (2.1-m diameter and 0.6-m height) to mimic a drinker failure. The pasture had only one location with livestock water, which was placed within an 80 × 150 m fenced area (water lot, Fig. 1) with two open access gates from the pasture in northeast and northwest corners of the water lot. Panels were used to simulate water failure so that livestock could readily access water at the end of the 4 h of water restriction by removing the panels. During 2019, a second smaller tank (1.0 × 1.5 × 0.6 m, 568 L) was placed in the water lot about 10 m from the primary water tank. The smaller water tank was empty and accessible to cattle during simulated water failure (trials) and full of water on other days (controls). During 2018, cows were observed pushing against the panels, which may not adequately simulate an empty tank. In 2019, the second tank was placed in the water lot to observe if cows behaved differently with access to an empty tank. Livestock were continuously monitored by trained researchers during water deprivation to detect animal stress, excessive dehydration, and heat stress in accordance with the approved IACUC protocols.

Cattle could enter the water lot at any time. If cows with functional GPS collars and/or accelerometers entered the water lot after 1100 h on water-failure simulation days, the data for that cow were not used in the analyses. Cows entering the water lot after
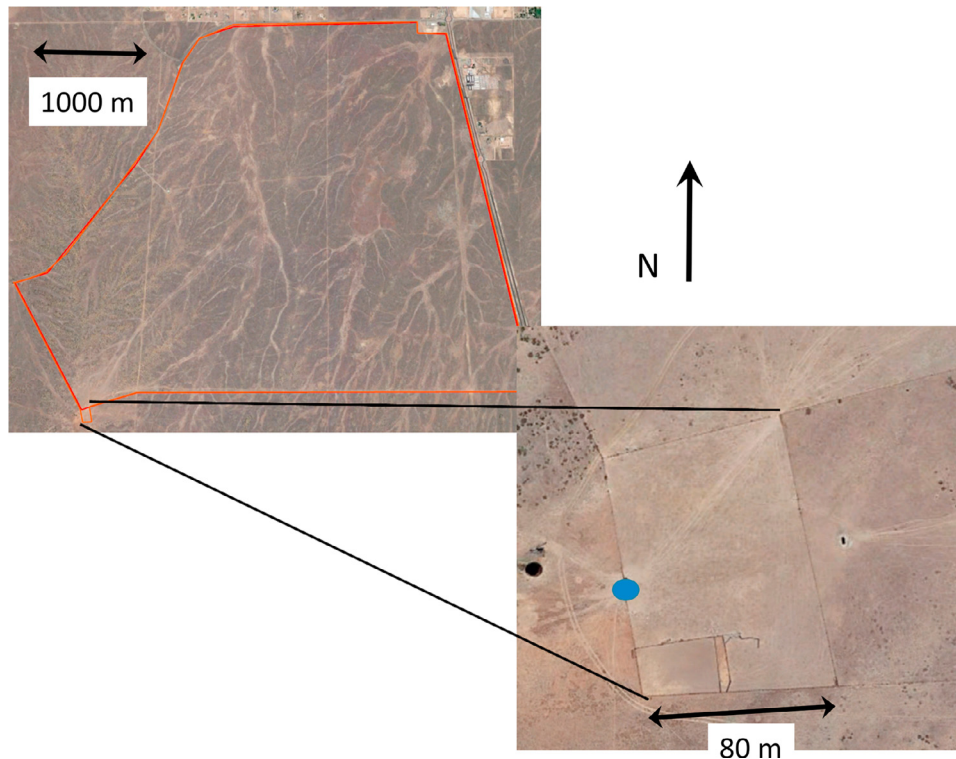
Fig. 1. Layout and location of watering lot (80 × 150 m) and water tank in the North Pasture at the Deep Well Ranch. The primary water tank (1 900 L) is indicated by a *blue circle.* Metal panels were used to prevent cattle from accessing the water tank and drinking (water system failure simulation). In the second yr of the study (2019), a smaller tank was placed about 10 m south from the primary tank and was empty on water failure simulations and full other days (controls).

1100 h had < 1 h of water deprivation and may have not displayed the same behaviors as cows entering the water lot earlier. Tracking data that were recoded after the water system failure simulation ended and the panels around the water tank were removed (or the similar period on control days) were not included in the analyses. Hours after water lot entry was used as a variable in the analysis. Hour 0 was the first hour after the cow entered the water lot during simulated water system failure (0800−1200 h) and on control days. Entry into the water lot was determined using GPS tracking data. Once cows were < 100 m from water, they had entered the water lot.

Data processing and feature extraction

The position data from GPS tracking and the movement data from the accelerometers were stored in memory on the devices. Tracking collars and ear tags with accelerometers were removed from the cows after the last trial each year.

Accelerometer data processing

Raw data from the accelerometers were downloaded as a .CWA file and converted to .CSV using OmGUI software provided from Axivity, Inc. Movement data from each axis (x, y, and z) were aggregated into 1-min epochs using Anaconda Python 3.7 (Anaconda, Inc, Austin, TX). The mean, maximum, minimum, and standard deviation of the epoch were calculated for each axis (x, y, and z). Movement intensity (MI) and signal magnitude area (SMA) were calculated for each accelerometer reading and averaged for the epoch (Table 1; Tobin et al. 2020). The range (absolute value of the maximum minus minimum) of MI and SMA were also calculated for each epoch.

Table 1
Metrics calculated from raw X, Y, and Z acceleration mean values from 1-min epochs. One-min epochs represent 720 data points, which is equivalent to T at the 12.5 Hz sampling frequency.

Feature	Equation
Average X-Axis (Ax)	$Ax = \frac{1}{T} \sum\limits_{t=1}^{T} x(t)$
Average Y-axis (Ay)	$Ay = \frac{1}{T} \sum\limits_{t=1}^{T} y(t)$
Average Z-axis (Az)	$Az = \frac{1}{T} \sum\limits_{t=1}^{T} z(t)$
Movement intensity (MI)	$MI = \frac{1}{T} \sum\limits_{t=1}^{T} \sqrt{(Ax^2) + (Ay^2) + (Az^2)}(t)$
Signal magnitude area (SMA)	$SMA = \frac{1}{T} (\sum\limits_{t=1}^{T} |\mathbf{Ax(t)}| + \sum\limits_{t=1}^{T} |\mathbf{Ay(t)}| + \sum\limits_{t=1}^{T} |\mathbf{Az(t)}|)$

Animal behavior

Animal behavior was visually observed and recorded using Samsung Tab E (Seoul, South Korea) notepads with a timestamp into an *Excel* datafile and manually written using a cellphone for time keeping. The Samsung tablet, cellphone, and laptop time were synchronized. Focal animal sampling was used for animal observations (Lehner 1996). Randomly selected cows that had both accelerometer and GPS units were observed with binoculars for 4−6 h each day. Visual observations were recorded on all 5 trial d and 6 nontrial d.

Behavior observations recorded include walking, grazing, lying, standing, drinking, and running. Standing and lying behaviors were classified as nonactive behaviors while grazing and walking were considered active behaviors. Running and drinking behaviors were observed infrequently, and both were removed from the analyses. Cattle that were observed lying often had slight head movements and rumination. Standing behavior was recorded when the animal

was upright with no major body movements except for slight head movements and rumination. Walking behavior was recorded when the animal proceeded in continual locomotion, generally in a linear path, and steady pace with its head in a level to up position. Grazing was recorded when the head was down manipulating or biting grasses, forbs, or shrubs. Grazing also included animal reorientations that took < 10 s between bites. Walking and grazing behaviors began after visual observations were constant for 15 s. Behavior recordings were terminated when changes in behavior observations were apparent.

GPS data processing

Cattle locations from the GPS collars were downloaded into @Trip PC software (Mobile Action Technology Inc., Taipei, Taiwan). Positions that were located outside of the study pasture were deleted from the data set. In addition, positions with unusual course deviations (> 100°) and velocity rates that are greater than an average walking speed for cattle (84 m/min; Chapinal et al. 2009) were likely inaccurate and were also removed from the data (Knight et al. 2018b). Positions obtained during the days that collars were placed on the cows or removed from the cows were excluded before analysis. Tracking data were used to determine distance from water and when animals entered and left the watering area (within 150 m of drinker location) using the Euclidean distance feature of ArcGIS version 10.7.1 (Redlands, CA). Distance from water (m), velocity (m/min), and distance traveled after watering event were averaged each hour (1-h intervals) for the day before and the day of simulated water delivery failure. Predicted animal behaviors were calculated directly from the tracking data (velocity) using the following criteria: resting (velocity < 2.34 m/min), grazing (velocity = 2.34–25 m/min), and traveling (velocity > 25 m/min) were calculated from GPS velocities (Augustine and Derner 2013; Nyamuryekung'e et al. 2020). Predicted active behavior was calculated by summing these traveling and grazing predicted behaviors (% active) and summarized by hour.

Statistical analyses

Tracking metrics (distance from water, velocity, GPS-predicted activity, and distance traveled after watering event) were analyzed using the repeated measures procedure of PROC MIXED in SAS (Littell et al. 2006). The fixed effects in the model included day of trial where d 0 is the day animals were restricted from water and d −1 is the day before water restriction, hours after water lot entry (0−hour the cow entered the water lot to 3–3 h after the cow entered the water lot), interaction of day and hours after water lot entry, and trial 1 to 5 (1 to 3 = trials in 2018 and 4 and 5 = trials in 2019). Cow was used as random effect since the same cow was used for all the trials in a given year. The subject of the repeated measures was cow within trial. Covariance of repeated records was modeled using the autoregressive order of 1 (AR1) covariance structure. The AR1 structure was used because the Akaike's Information Criteria (AIC) value was lower than the other covariance structures evaluated, compound symmetry and unstructured (Littell et al. 2006).

Linked observational behaviors and accelerometer metrics (see Table 1) were analyzed using the random forest procedure PROC HPFOREST in SAS (SAS Institute Inc., NC; Nord and Keeley 2016). A training set of 305 known observations was used to create a prediction model within the HPFOREST procedure. Prediction metrics include x-mean, y-mean, z-mean, MI-mean, SMA-mean, MI-minimum, MI-maximum, MI-variance, and MI-range. Behavior predictor metrics include individual animal behaviors, and animal activity were predicted using PROC SCORE. Using the prediction model, the entire dataset of 57 600 1-min epochs from 11 accelerometer devices was analyzed to determine daily

behavior and activity budgets. Because of the limited number of visual observations, the training data set was also used in validation.

Random forest predicted animal activity behavior metrics from accelerometer data and accelerometer axes (x, y, and z), and MI means were analyzed using the repeated measures procedure of PROC MIXED (Littell et al. 2006). Before these analyses, accelerometer data were averaged by hour. The fixed effects in the model included day of trial where d 0 is the day animals were restricted from water and d −1 is the day before water restriction, trial 1 to 5 (1 to 3 = trials in 2018 and 4 and 5 = trials in 2019), and hour of the day (0800−1300 h) and the interactions of day and hour. Cow was included as a random effect. The subject of the repeated measures was cow within trial. Covariance of repeated records was modeled using the AR1 covariance structure. The AR1 structure was used because the AIC value was lower than the other covariance structures evaluated, compound symmetry and unstructured (Littell et al. 2006). Hour that the cow entered the water lot could not be used as a fixed effect for accelerometer data because the GPS tracking data were not available for all cows with accelerometers (the GPS units failed).

Results

Weather for trial day and the previous watering event were relatively similar, except for Trial 3 (Table 2). The daily maximum temperature was 28.8°C for the simulated watering event on Trial 3 and 21.2°C for the previous day.

Accelerometer metrics

Using PROC HPFOREST, SAS machine learning techniques created behavior predictions. This model included a validation set of 305, 1-min epoch observations with a misclassification rate of 24.6%. Top metrics used for machine learning procedures and behavior predictions were Y mean, Z mean, MI mean, MI min, and MI max with out-of-bag Gini values of 0.059, 0.025, 0.008, 0.002, and −0.001, respectively.

No differences in active behavior predictions (grazing and walking), from random forest machine learning, were detected between days of the trial ($P = 0.49$), among hours of the day (0800 to 1300, $P = 0.99$), and among trials ($P = 0.70$). In addition, no interaction between day and hour was detected ($P = 0.96$).

Movement intensity was greater ($P = 0.03$) on the day of simulated water failure than the previous day (Fig. 2). Movement intensity also varied among trials ($P = 0.01$). Movement intensity tended to vary ($P = 0.07$) among hours of the day (0800 to 1300) with the highest mean activity at 0800 h and the lowest level at 1000 h.

Epoch-long averages of axis movement yielded similar results. The average of y axis (side to side) was greater ($P = 0.03$) on the day of simulated water failure than the previous day. The y axis also varied among trials ($P < 0.001$). No differences ($P = 0.60$) among hours of the trial (0800 to 1300) were detected. Also, no interaction between day and hour ($P = 0.062$) was detected.

No differences in the z axis (front to back) among trials ($P = 0.66$), between days of the trial ($P = 0.48$), or the interaction of day by hour ($P = 0.84$) were detected. The z-axis varied ($P = 0.05$) among hours. The most movement in the z-axis was at 0800, and the least was at 1000.

GPS metrics

There was a strong interaction ($P = 0.01$) between day and the hour the animal entered the watering lot for distance to water (Fig. 3). During the previous watering event (normal watering event) animals would enter the watering area, drink, and exit the

Table 2
Average monthly temperature range and weather conditions for each simulated water failure trial. Each trial contains the daily high temperature (°C) and precipitation (mm) from the previous watering event (d −1) and simulated water failure event (d 0).

Trial	Previous watering date	Previous wateringday high temperature (°C)	Previous wateringday precipitation(mm)	Simulated failure date	Simulated failureday high temperature (°C)	Simulated failureday precipitation (mm)	Average monthly temperature range(1971-2000) (°C)
1	6/5/2018	36.1	0.0	6/6/2018	33.8	0.0	12.5-36.1 ± 0.33
2	6/11/2018	32.2	0.0	6/12/2018	35.5	0.0	12.5-36.1 ± 0.33
3	6/17/2018	21.1	4.5	6/18/2018	28.8	0.0	12.5-36.1 ± 0.33
4	7/16/2019	37.7	0.0	7/17/2018	37.2	0.0	16.4-37.2 ± 0.21
5	7/18/2019	34.4	0.0	7/19/2018	36.1	0.0	16.4-37.2 ± 0.21
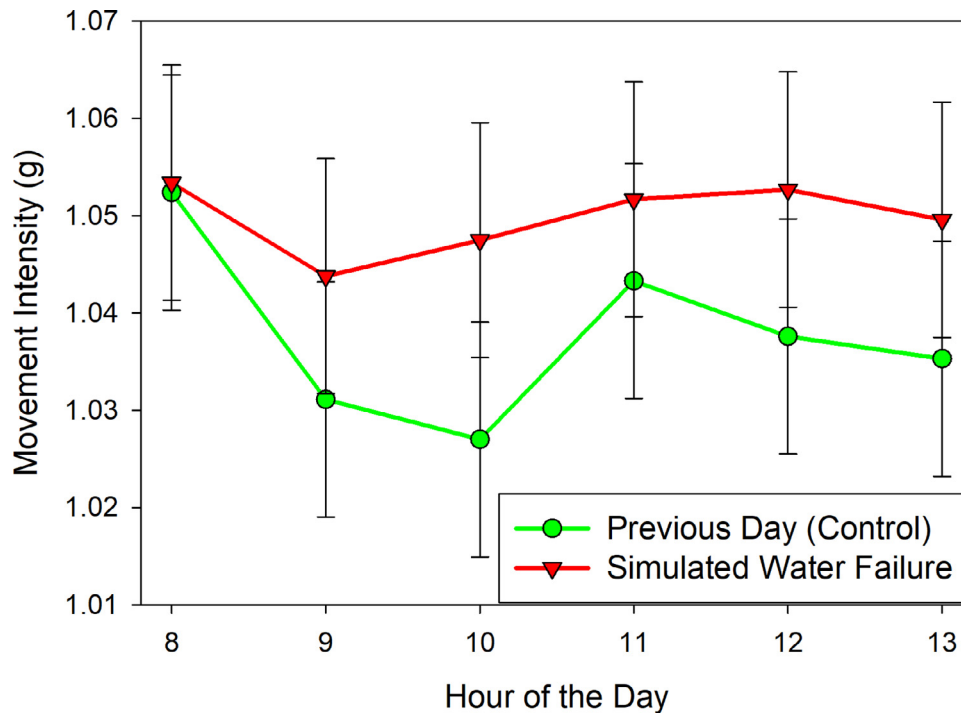
Fig. 2. Hourly means (0800−1300 h) of movement intensity during the morning and early afternoon when water was restricted (d 0) and during the previous watering event (control, d −1). Error bars represent standard errors. During the day of simulated water system failure, movement intensity was greater than the previous day ($P = 0.03$).

watering area within a short period of time (< 5 min). During simulated watering failure, the minimum distance from water remained lower than during the previous watering event from the time the animals entered the watering lot and continued for the next 3 h.

Velocity of travel was greater ($P < 0.001$) during the hour cows entered the water lot. No differences between days ($P = 0.23$), trials ($P = 0.10$), or the interaction of day by hour entering the water lot ($P = 0.48$) were detected. During the simulated water failure, the velocity drops after the first hour within the water lot and continues to remain low during the remaining 3 h.

Cows were more active ($P < 0.001$) during the hour (h 0) the animal entered the water lot ($P < 0.0001$) based on active behavior predicted from GPS velocity. No differences among trials ($P = 0.38$), days ($P = 0.68$), or the interaction of day by hour ($P = 0.21$) were detected.

Results from activity were mirrored for the GPS prediction of resting. Cows rested less ($P < 0.001$) during the hour (h 0) the animal entered the water lot. No differences among trials ($P = 0.38$), days ($P = 0.68$), or interaction of day by hour ($P = 0.21$) were detected.

The percentage of time traveling was greater ($P < 0.001$) during the hour cows entered the water lot. There were also differences among trials ($P = 0.03$) for the GPS prediction of traveling. No differences between days ($P = 0.31$) or interaction of day by hour ($P = 0.12$) were detected.

No differences in GPS predicted grazing time were detected for the hour the animal entered the water lot ($P = 0.37$), trial ($P = 0.09$), day of trial ($P = 0.91$), or the interaction of day by hour ($P = 0.10$) were detected. During normal watering events and simulated water failure trials, animals normally did not graze immediately post watering.

Discussion

On the day of the simulated water failure, the distance from water clearly differed from normal watering events. Distance from water during the hour periods (0−4 h) after first entering the water lot when water access was restricted was much less than the previous day when cattle watered normally. Observations during the study suggested that cattle typically entered the watering area, drank and moved away from the tank after 4 min, and then started traveling to resting areas located at least 250 m from water near or under shade and rested and/or ruminated. Cows would remain in these areas until their evening grazing bout beginning about 1600 h. Tracking data support these visual observations because cows consistently moved away from the water lot after drinking at the tank every day but on simulated water failures.

In contrast to typical watering events, cows would enter the watering area on simulated water-failure days, ascertain that water was not available, and move within the watering area, but they did not go farther than 150 m from the water drinker (within the wa-
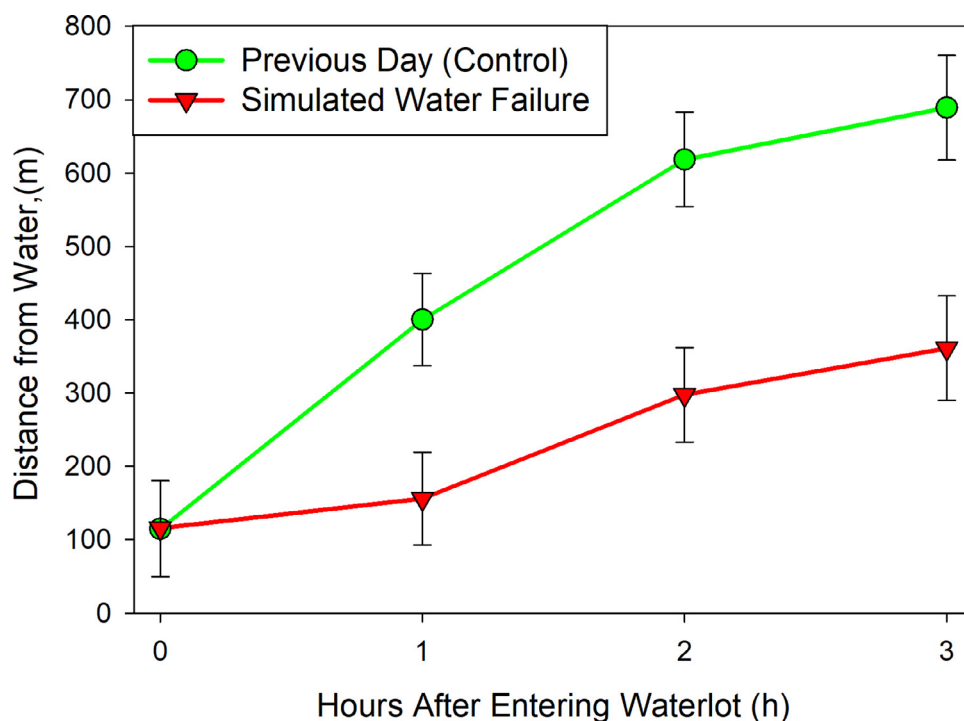
Fig. 3. Hourly means of distance from water during the 4 h of simulated water system failure when cows were prevented from accessing water (0800–1200 h) and the same time period on the previous day (control). The x-axis displays the hours after entering the water lot, which began (0 h) when Global Positioning System (GPS) tracking showed that the cow was ≤ 150 m from water. Visual observations confirmed that GPS-tracked animals were going to and entered the water lot. Distances from water after entering the water lot varied (P = 0.01) among days (day of water deprivation vs. the previous day). Error bars represent standard errors.

ter lot, Fig. 1). During the time of water restriction, observers noted that livestock would tend to move around the water lot and appeared to become increasingly aggressive with other cattle, mainly the calves, by hitting them with their horns. The increase in MI during the period of water restriction (Fig. 2) is likely a consequence of these observed aggressive behaviors. This may help explain why predicted behavior performed poorly compared with MI and individual axes from the accelerometer data. Aggressive behavior was not used in random forests classification of accelerometer data.

Velocity (distance traveled per hour) was relatively similar on the day of water restriction compared with days without water restriction. This is likely due to livestock remaining in the watering area moving small distances rather than normal traveling to nearby shaded areas for resting (< 300 m from drinker). Apparently, movement within the water lot on days of simulated water failure was equivalent to the travel to resting areas after watering (normal behavior).

Movement intensity levels monitored during simulated water delivery failure were higher than during normal watering events. Since cattle normally water at midday (Gregorini 2012; Williams et al. 2019), a change in activity at midday may be helpful in detecting water availability issues. The use of near-real-time and real-time accelerometer systems such as HerdDogg (Ashland, OR, https://www.herddogg.com/) and Moonitor (Israel, https://www.moonitorcows.com/) could be helpful in determining water system failures earlier than managers and caretakers might normally observe. However, hourly differences in MI between simulated water failure and control days could not be detected, which is likely because of the variability among hours and cows. Only differences in days were detected for MI and other accelerometer metrics, which suggests measurements on multiple cows collected over a few hours may be required to detect water system failures. Short-term movements may not be detected by coarse GPS tracking with

longer intervals between positions; however, if cattle remain near water after system failure, even coarse tracking (e.g., position every hour) should be able to detect a water availability problem within a few hours. Remote monitoring using accelerometers and GPS tracking might detect changes in behavior faster than GPS tracking alone, especially if there were long intervals between location fixes. When water systems fail, it is critical for managers to address the problem and repair the water system quickly, especially in hot weather.

No trial dates had temperature values outside of the normal average monthly range. Though weather for trial 3 was cooler than the remaining trials, the pair of dates associated with trial 3 were both cooler and overcast. Across all study parameters, there were no consistent differences among trials. In trials 4 and 5, cows could access a second smaller tank that was empty on simulated water-failure days. No differences were detected between trials 4 and 5 (with a second tank) and trials 1, 2, and 3 (without a second tank). The similarity of cattle behavior (increased activity and remaining near the water tank during simulated water system failure) in variable weather, with and without access to a second (empty or full) tank, supports the use of on-animal sensors as a tool for real-time monitoring of water availability.

All animals that entered the water lot remained near water during simulated water failure. Due to IACUC protocols and animal well-being concerns, the trials were ceased after 4 h of water deprivation and before the onset of more extreme behavioral indicators. The effects of water deprivation on cattle health may not be critical until 24 h of deprivation, when there will be a loss of appetite and mobilization of body fat reserves (Marques et al. 2012). After 24 h of water restriction, the effects of dehydration will become more critical. Cows can lose over 20% of their body weight within 3 d and will likely expire within 5 d of water deprivation (Siebert and Macfarlane 1975). Water system failure should be addressed immediately to maintain animal well-being.

Real-time GPS tracking systems are being developed, and some, such as Moovement (Brisbane, Queensland, Australia, https://www.moovement.com.au/), are commercially available. Moovement GPS ear tags record locations every 60 min and could potentially detect water system failure within 2−4 h after cattle travel to water on the basis of the results of this study. Other livestock monitoring systems that can detect proximity of a device in real time potentially could be used to remotely monitor water system failures. However, the system would need to detect devices at distances of 100−150 m on the basis of this study. Passive ultra-high frequency (UHF) radio frequency identification (RFID) tags have a useful range of 10−20 m, and active tags have a range over 100 m (Byondi and Chung 2019). Another method to reduce the cost for purchasing an on-animal tracking and sensor monitoring system for water system failures would be to place devices on a limited number of sentinel animals rather than on the entire herd. More research is needed to estimate the number of sentinel animals needed because sample size needed will be at least partially determined by the capabilities of the tracking and sensor devices and the frequency that the data can be transferred from animals to the producer using LoRa WAN or similar systems.

Remotely monitoring for water system failures, such as well failure, water line blockage or rupture, and water tank float/valve issues, could allow producers to respond more rapidly and perhaps reduce the time spent manually checking water systems. Decreasing this response time could lessen the adverse impacts such as lower volumes of water and other body fluids due to dehydration (Siebert and MacFarlane 1975). This approach is based on the concept of cattle remaining near water tanks when they are empty or animals being prevented from accessing the tank (simulation in this study). However, this system would not detect when a float or valve failed and the tank would overfill, which could potentially empty the water storage reservoir.

Individual variation in animal behavior can reduce the accuracy of behavior predictions from sensors on livestock. Bailey et al. (2018) mention that the variability between animal individuals' movement patterns will continue to be a rich area of behavior research. It will be essential for sensor technology to identify changes in individual behavior rather than quantifying a set threshold for a given behavior or welfare issue. The variation among cows for MI and other accelerometer metrics in this study supports the concept of monitoring changes in individual cows rather than developing thresholds. Improving prediction models on the basis of changes in individual behavior could improve more rapid detection of welfare issues such as disease (Tobin et al. 2020).

Management implications

Technological advancements will likely increase the use of real-time and near real-time livestock sensors including GPS and accelerometers. The proof of concept described in this paper demonstrates the potential to use real-time or near-real-time GPS tracking and accelerometers to remotely monitor livestock welfare issues, such as water system failures. Increased time spent near water (e.g., < 150 m) and increased levels of activity during period cattle normally water are possible indicators of water delivery failures in rangeland pastures. Remote detection of water system failures could reduce the response time for ranchers to repair the water system, which would improve livestock well-being. In addition, an on-animal tracking and monitoring system might reduce the frequency that on-site checks of livestock water would be required and correspondingly reduce labor inputs.

References

Alvarenga, F.A.P., Borges, I., Palkovic, L., Rodina, J., Oddy, V.H., Dobos, R, 2016. Using a three-axis accelerometer to identify and classify sheep behaviour at pasture. Applied Animal Behavioural Science 181, 91–99.

Anderson, D.M., Estell, R.E., Cibils, A.F., 2013. Spatiotemporal cattle data—a plea for protocol standardization. Positioning 04, 115–136.

Anderson, D.M., Kothmann, M.M., 1977. Monitoring animal travel with digital pedometers. Journal of Range Management 30, 316.

Augustine, D.J., Derner, J.D., 2013. Assessing herbivore foraging behavior with GPS collars in a semiarid grassland. Sensors (Switzerland) 13, 3711–3723.

Bailey, D.W., 2016. Grazing and animal distribution. In: Villalba, J.J. (Ed.), Animal welfare in extensive production systems. 5M Publishing, Sheffield, UK, pp. 59–81 The Animal Welfare Series.

Bailey, D.W., Trotter, M.G., Knight, C.W., Thomas, M.G., 2018. Use of GPS tracking collars and accelerometers for rangeland livestock production research. Translational Animal Science 2, 81–88.

Barwick, J., Lamb, D., Dobos, R., Schneider, D., Welch, M., Trotter, M., 2018. Predicting lameness in sheep activity using tri-axial acceleration signals. Animals 8, 1–16.

Byondi, F.K., Chung, Y, 2019. Longest-range UHF RFID sensor tag antenna for IoT applied for metal and non-metal objects. Sensors (Basel) 19, 5460.

Chapinal, N., De Passille, A., Weary, D., Von Keyserlingk, M., Rushen, J., 2009. Using gait score, walking speed, and lying behavior to detect hoof lesions in dairy cows. Journal of Dairy Science 92, 4365–4374.

Fogarty, E.S., Swain, D.L., Cronin, G., Trotter, M., 2019. Autonomous on-animal sensors in sheep research: a systematic review. Computers and Electronics in Agriculture 150, 245–256.

Fogarty, E.S., Swain, D.L., Cronin, G.M., Moraes, L.E., Trotter, M., 2020. Behaviour classification of extensively grazed sheep using machine learning. Computers and Electronics in Agriculture 169, 105175.

Gregorini, P., 2012. Diurnal grazing pattern: its physiological basis and strategic management. Animal Productivity Science 52, 416–430.

Herbel, C., Ares, F., Nelson, A, 1967. Grazing distribution patterns of Hereford and Santa Gertrudis cattle on southern New Mexico range. Journal of Range Management 20, 269–298.

Herbel, C.H., Nelson, A.B., 1966. Activities of Hereford and Santa Gertrudis Cattle on a southern New Mexico range. Journal of Range Management 19, 173–176.

Knight, C.W., Bailey, D.W., Faulkner, D., 2018a. Low-cost global positioning system tracking collars for use on cattle. Rangeland Ecology & Management 71, 506–508.

Knight, C.W., Bailey, D.W., Grubb, K., Mandeville, W., Wilker, J., 2018b. Data correction and analysis of spatial data using lower-cost global positioning system tracking collars. In: Proceedings of the 71st Society of Range Management. Sparks, NV, USA.

Lehner, P.N., 1996. Handbook of ethological methods. Cambridge University Press, Cambridge, United Kingdom, p. 672.

Littell, R.C., Milliken, G., Stroup, W., Wolfinger, R., Schabenberger, O., 2006. SAS for mixed models. SAS Institute, Cary, NC, USA, p. 814.

Maroto-Molina, F., Navarro-García, J., Príncipe-Aguirre, K., Gómez-Maqueda, I., Guerrero-Ginel, J.E., Garrido-Varo, A., Pérez-Marín, D.C., 2019. A low-cost IoT-based system to monitor the location of a whole herd. Sensors 19, 2298.

Marques, R.S., Cooke, R.F., Francisco, C.L., Bohnert, D.W., 2012. Effects of twenty–four hour transport or twenty-four hour feed and water deprivation on physiologic and performance responses of feeder cattle. Journal of Animal Science 90, 5040–5046.

McLennan, K.M., Skillings, E.A., Rebelo, C.J.B., Corke, M.J., Pires Moreira, M.A., Morton, A.J., Constantino-Casas, F., 2015. Technical note: Validation of an automatic recording system to assess behavioural activity level in sheep (Ovis aries). Small Ruminant Research 127, 92–96.

Nord, C., Keeley, J, 2016. An introduction to the HPFOREST procedure and its options. Midwest SAS Users Group Conference Proceedings; Cincinnati, OH. Paper AA20. Available at: https://www.mwsug.org/proceedings/2016/AA/MWSUG-2016-AA20.pdf, Accessed March 22, 2021.

Nyamuryekung'e, S., Cibils, A.F., Estell, R.E., VanLeeuwen, D., Steele, C., Estrada, O.R., Almeida, F.A.R., González, A.L., Spiegal, S, 2020. Do young calves influence movement patterns of nursing Raramuri Criollo cows on rangeland? Rangeland Ecology & Management 73, 84–92.

Roath, L.R., Krueger, W.C., 1982. Cattle grazing and behavior on a forested range. Journal of Range Management 35, 332–338.

Sanchez-Iborra, R., Sanchez-Gomez, J., Ballesta-Viñas, J., Cano, M.-D., Skarmeta, A., 2018. Performance evaluation of LoRa considering scenario conditions. Sensors 18, 772.

Siebert, B.D., MacFarlane, W.V., 1975. Dehydration in desert cattle and camels. Physiology and Zoology 48, 36–48.

Terrasson, G., Llaria, A., Marra, A., Voaden, S., 2016. Accelerometer based solution for precision livestock farming: geolocation enhancement and animal activity identification. IOP Conference Series: Materials Science and Engineering 138, 012004. doi:10.1088/1757-899X/138/1/012004.

Tobin, C., Bailey, D.W., Trotter, M.G., Connor, L.O., 2020. Sensor based disease detection: a case study using accelerometers to recognize symptoms of bovine ephemeral fever. Computers and Electronics in Agriculture 175, 1–5.

Turner, L.W., Udal, M.C., Larson, B.T., Shearer, S.A., 2000. Monitoring cattle behavior and pasture use with GPS and GIS. Canadian Journal of Animal Science 80, 405–413.

Williams, L.R., Fox, D.R., Bishop-Hurley, G.J., Swain, D.L., 2019. Use of radio frequency identification (RFID) technology to record grazing beef cattle water point use.pdf. Computers and Electronics in Agriculture 156, 193–202.