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# Validation of proximity loggers to record proximity events among beef bulls

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## Abstract

Social behavior in cattle can be measured by how often and for how long they interact with each other. This information can be used to guide management decisions, identify sick animals, or model the spread of diseases. However, visual observation of proximity events is time-demanding and challenging, especially for rangeland cattle spread over a large area. Although proximity loggers can potentially overcome these challenges remotely, it is unknown how accurate these devices are in recording proximity events among beef bulls. The objectives of this study were: 1) to determine the accuracy of Lotek LiteTrack LR collars with built-in proximity loggers to identify proximity events among bulls and 2) to determine the accuracy of Lotek LiteTrack LR collars to identify proximity events between bulls wearing collars and bulls wearing the Lotek V7E 154D ear tag proximity transmitter. Collars were deployed in 12 bulls in 2021 (Experiment 1), and 10 bulls (5 collars and 5 ear tags) in 2023 (Experiment 2). Videos were recorded of bull behavior in both years to compare proximity observed to proximity recorded by the loggers. Sensitivity (Se), specificity (Sp), precision (Pr), and accuracy (Ac) were calculated after computing true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN). The interquartile range method was used to detect outliers. As collars work as both a transmitter and receiver in Exp. 1, reciprocity was assessed by the Concordance Correlation Coefficient (CCC) as an indirect measure of reliability. In Exp. 1, most observations were TN (95.13%), followed by FN (4.11%), TP (0.70%), and FP (0.06%). A high Sp (median = 1.0; 95% CI = 1.0 to 1.0), Pr (1.00; 0.72 to 1.0), and Ac (0.96; 0.95 to 0.97), and low Se (0.10; 0.06 to 0.21) were observed. A high reciprocity agreement (0.93; 0.89 to 0.96) was also observed. Likewise, in Exp. 2 most observations were TN (85.05%), followed by FN (9.94%), TP (4.36%), and FP (0.65%), while high Sp (0.99; 0.99 to 1.0), Pr (0.89; 0.80 to 0.92), and Ac (0.95; 0.81 to 0.95), and low Se (0.35; 0.24 to 0.61) was observed. The Pr of two loggers in Exp. 1 and Pr and Ac of one logger in Exp. 2 were considered outliers. In conclusion, both proximity loggers demonstrated high precision, specificity, and accuracy but low sensitivity in recording proximity among beef bulls. Therefore, these characteristics should be considered when deciding whether to use these devices or not.

## Lay Summary

Understanding cattle's social behavior can enhance productivity and welfare by informing management practices to improve maternal care, disease control, and identifying mating behaviors to assess bull performance, among other applications. However, visual observation of a herd is challenging and time-demanding task, especially for rangeland cattle. Proximity loggers can reduce the dependency on visual observation through remote proximity monitoring, but little is known about their reliability for beef bulls on pasture. This study aimed to validate remote monitoring loggers to detect the proximity of beef bulls within 2.5 to 3 m of each other. Two experiments were performed to determine proximity measurement among collars and between collars and ear tags. Videos were recorded as the gold standard to which the loggers were compared, and reciprocity between collars was analyzed as an indirect measure of reliability. Loggers presented high precision, low sensitivity, and high reciprocity. This indicates that the loggers will not record most proximity events, but those recorded are highly reliable. Additionally, based on reciprocity analysis, the collars worked properly as receivers and transmitters. In conclusion, these loggers may be used to investigate social interactions between bulls, but the low sensitivity should be considered in the decision of its use.

**Key words:** beef cattle, bull behavior, precision livestock technologies, proximity, reciprocity, social behavior

## INTRODUCTION

Understanding how often and for how long individuals in a herd are in proximity to each other provides insightful information about their social behavior (Fielding et al., 2021). This information can be used to guide management decisions to enhance cattle productivity and welfare (Nogues et al., 2023), and for modeling the spread of diseases (de Freslon et al., 2019). For instance, proximity was used to investigate cow-calf and bull-cow interactions with the potential to quantify maternal and mating behaviors (Swain and Bishop-Hurley, 2007; O'Neill et al., 2014), and to identify sick steers based on their proximity with other steers and to water and feed trough (White et al., 2023). Similarly, proximity among dairy cows was shown to be a risk factor for disease transmission (de Freslon et al., 2019), with management practices altering proximity patterns and playing a role in mitigating outbreak occurrence (Fielding et al., 2021).

A growing interest in remote monitoring technologies for cattle has been observed over the years and across the world (Besler et al., 2024), given their potential to gather detailed data at the individual level (Tedeschi et al., 2021) with reduced dependency on human observation (Bailey et al., 2021). Behaviors can be monitored remotely through different technologies, with particular benefits for animals on

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rangelands, where direct observations are difficult (Bailey et al., 2021). These difficulties increase when studying the social behavior of cattle, as understanding their social dynamics requires observing multiple individuals interacting within a herd (Hubbard et al., 2021). Furthermore, it is known that the presence of an observer can influence the social behavior of some animals and bias the observations due to the different levels of tolerance (Allan et al., 2022). Therefore, proximity loggers have the potential to measure aspects of the social behaviors of free-range cattle with minimal dependency and influence of human observation. However, they can also increase the data collection costs (Ryder et al., 2012), which makes it important to explore the validity of proximity logger systems with different costs (e.g., more expensive systems using exclusively transmitter-receiver collars or less expensive ones using a mix of receiver collars and transmitter ear-tags).

As observed by Besler et al. (2024), radio frequency devices, such as proximity loggers, are one of the less studied devices among precision technologies for cattle monitoring. Although these devices have been used to investigate beef cattle social behavior aspects, such as cow-calf interactions (Swain and Bishop-Hurley, 2007), cow-cow interactions (Swain et al., 2015), or cow-bull interactions (O'Neill et al., 2014), little is known about their accuracy in recording proximity events. Most studies assessing the accuracy of proximity loggers were conducted in laboratory settings (Prange et al., 2006; Drewe et al., 2012) or with horses (Milwid et al., 2019; Ossi et al., 2022), deer (Ossi et al., 2022), raccoons (Prange et al., 2006), badgers, and badger-cow interactions (Drewe et al., 2012). Amongst those studies in cows, they either did not validate their results with a gold standard test, such as visual observations (Watson-Haigh et al., 2012), or used a short period of observations in their field analysis (Drewe et al., 2012).

Therefore, it is unknown how accurate these devices are in recording proximity among beef bulls. As the animal's body mass can cause several interference phenomena on radio signal propagation (Swain et al., 2015; Fielding et al., 2021), it is important to assess the device's accuracy on animals with similar body mass as the ones the loggers will be deployed (Triguero-Ocaña et al., 2019). Inferring accuracy from validation studies on different species will likely lead to unrealistic results (Triguero-Ocaña et al., 2019). Therefore, the objectives of this study are: 1) to determine the accuracy of Lotek LiteTrack LR collars with built-in proximity loggers to identify proximity events among bulls and 2) to determine the accuracy of Lotek LiteTrack LR collars to identify proximity events between bulls wearing collars and bulls wearing the Lotek V7E 154D ear tag proximity transmitter.

## MATERIALS AND METHODS

The experimental protocols were approved by the University of Calgary Veterinary Services Animal Care Committee (VSACC) under animal care protocol #AC20-0018. All experiments were conducted at the WA Ranches at the University of Calgary in Rocky View County, Alberta, Canada.

### Devices and Animals

The devices used in the study were the Lotek LiteTrack LR collar and the Lotek V7E 154D ear tag (Lotek Wireless Inc., Newmarket, Ontario, Canada). The collar has built-in transmitter and receiver proximity sensors in addition to Global Positioning System (GPS), accelerometer, and onboard storage capacity. The ear tag only contains a transmitter proximity sensor and no storage capacity. Both devices operate at very high frequencies (VHF; [150.82 MHz]), and the proximity events are registered based on a Received Signal Strength Indicator (RSSI) threshold. The RSSI value is a proxy for the maximum distance from which the receiver perceives a transmitter, and this value is pre-set during device programming. Each device (collar and ear tags) transmits a unique identification number that is perceived by receivers (collars) in the vicinity that register the identification number, the time in which the proximity started (moment in which the RSSI value becomes stronger than the pre-set threshold) and stopped (moment in which the RSSI value becomes weaker than the pre-set threshold), the duration of the proximity event, and the average RSSI of the proximity event.

Collars and ear-tags were programmed to operate based on pre-set schedules using the Pinpoint Host Software (Lotek Wireless Inc., Newmarket, Ontario, Canada), which creates and uploads the schedules on the devices and downloads the data stored in the collars. In 2021, the schedules were set to operate from 000000 universal time coordinated (UTC) on June 3rd (Day 0) to 235959 UTC on June 17th (14 days total), and in 2023, from 000000 UTC on April 5th (Day 0) to 235959 UTC on April 18th (13 days total). The RSSI threshold value was set to −80 decibel-milliwatts (dBm), corresponding to a perimeter of 2.5 to 3m of distance (approximately one bull length). The transmitter burst rate (the rate at which identification numbers are transmitted) was set to 20 megabits per second (Mbps) for collars and 40 Mbps for ear tags, and the transmitter power (amount of power inputted on each transmission) was set to L4 (a scale ranging from L1 to L5 where L1 is the maximum power and L5 is the minimum power) for both loggers. A separation time of 1 min was set for collars, meaning that the proximity events will be accumulated in the same record until a separation of at least 1 min is detected; in that case, a new event is recorded.

All the abovementioned settings (RSSI = −80 dBm, transmitter burst rate = 20 Mbps, and transmitter power = L4) were selected based on manufacturer recommendations. The recommendations aimed to balance the range of proximity determined (one bull body length or approximately 2.5 to 3 m) and the operation and data storage generated by the three sensors contained in the collars (proximity, GPS, and accelerometer) for at least 60 days (approximately the duration of a breeding season). Although this study describes only the data recorded from the proximity loggers, the collars were also programmed to record three-dimensional GPS fixes (Latitude, Longitude, and Altitude) every 5 min, and accelerometers were set to operate at 0.5 Hertz (Hz) (2021) or 1 Hz (2023). Both followed the same schedules as the proximity loggers.

Once the devices were pre-set, collars were deployed on bulls in 2021 to study proximity events among 12 bulls wearing collars (Experiment 1) and in 2023 to study proximity events between five bulls wearing collars and five bulls wearing ear tags (Experiment 2). Collars and ear tags were deployed on animals while they were restrained in a squeeze chute. Collars were manufactured in two sizes with minimum and maximum adjustable sizes (95 to 117 cm and 118 to 127) to fit the variety of neck sizes of bulls. Therefore, after each bull was restrained in the squeeze chute, the neck was measured, and the collar size for that animal was decided. Then, a collar within the size range was placed around their necks, adjusting the tightness to leaving a maximum space of four centimeters between the internal face of the collar and the lateral of the animal's neck. Ear tags were applied using a regular livestock ear tag plier (Allflex® Universal Total Tagger) in an alternating pattern, with the first animal entering the chute receiving a randomly assigned ear tag and the next one not.

In 2021 (Experiment 1), 11 Aberdeen Angus and one Hereford bull (four 2-year-olds, four 3-year-olds, one 4-year-old, two 5-year-olds, and one 6-year-old) were enrolled in the study. After the collars were adjusted around their necks, they were housed in a dry lot pen (1.59 ha) from June 3rd to June 17th. All collars were set to transmit and receive signals during the entire period. This pen contained two wind-breaker panels attached in line (made of wooden boards with a metal frame; each one had an approximate height of 3 m and length of 7 m), one metal round hay bale feeder, one water trough, and one cattle groomer spread across the pen with at least 20 m from each other.

In 2023 (Experiment 2), 11 Aberdeen Angus bulls (two 3-year-olds, four 4-year-olds, one 5-year-old, two 6-year-olds, and two 7-year-olds) were enrolled in the study. Five bulls were housed in dry lot pen 1 (0.190 ha), and six bulls were housed in dry lot pen 2 (0.306 ha) from April 5th to April 18th. Each pen contained one round hay bale feeder, one water trough, and wind-breaker panels on the south and north boundaries of the pens by the limiting fences. No wind-breaker panels or cattle groomers were installed inside the pens. Bulls were randomly assigned to each pen after receiving ear tags and collars, stratified by age and ear tags within pens. Pen 1 housed one 3-year-old, two 4-year-olds, one 6-year-old, and one 7-year-old bull, with an average body weight of 860 ± 48 kg (range: 782 to 907 kg) and a stocking density of 2.26 kg/m$^2$. Pen 2 housed one 3-year-old, two 4-year-olds, one 5-year-old, one 6-year-old, and one 7-year-old bull, with an average body weight of 940 ± 73 kg (range: 821 to 1038 kg) and a stocking density of 1.84 kg/m$^2$.

Two bulls in pen 1 (one 4-year-old and one 6-year-old) and three bulls in pen 2 (one 3-year-old, one 4-year-old, and one 5-year-old) received ear tags in addition to the collars. The proximity function on these collars (five bulls with both collars and ear tags) was deactivated to avoid interferences and unnecessary draining of their batteries because these collars would be in close proximity with the ear tags for the entire period, generating no meaningful result for the study. These bulls received collars even though the interest of this study was to record proximity between ear tags and collars because the accelerometer and GPS data were collected for a different study. One bull in the group was excluded from experiment 2 due to excessive reactivity during handling (ear tag placement), in which he received a collar with the proximity function deactivated, no ear tag, and was housed in pen 2. Therefore, the final 2023 group included five bulls wearing collars with capabilities of receiving radio signals from the ear tags and five bulls wearing ear tags transmitting radio signals to collars other than themselves.

In both years, the animals were observed for 1 h after deploying the devices for signs of discomfort related to the device, such as panting, ear flicking, persistent head throwing, and persistently rubbing the collar against the fence.

## Visual Observations

Proximity events were identified using continuous video recordings of approximately 30 continuous minutes, starting at the Day 0 of each year, from 0800 to 1000 h or 1300 to 1400 h three times a week during weekdays in 2021 (experiment 1) and from 0800 to 1600 h five times a week during weekdays in 2023 (experiment 2). Two video cameras (Canon® Vixia HF R800) were set on tripods outside the pens, filming one or more bulls in the same frame. The cameras were positioned to have the focal bull or group of bulls in the frame with at least one bull body length (approximately 2.5 to 3 m) of the distance between their bodies and the edge of the frame. In 2021, both cameras were used but focused on different bulls or groups of bulls simultaneously, ensuring that not the same animals were recorded simultaneously for both cameras. In 2023, each camera was set to record one of the pens.

The first seconds of each video started by focusing on a stopwatch that was synched in time with the collars and ear tags' internal clock, giving the time reference to ensure that the observation would be associated with the correct proximity event. All videos recorded were uploaded into the software Boris v.7 (Friard and Gamba, 2016) and were analyzed to identify proximity events. Videos were watched focusing on one bull at a time, and bulls were considered in proximity when any bull entered a perimeter closer to one bull's body length (approximately 2.5 to 3 m) to a focal bull, regardless of who approached who. The distance of one bull's body length was chosen as a reference point for the observer to determine proximity, as it was not possible to measure the distance between two animals on the video because the distance from a bull to the video cameras varied. Once the proximity was identified, the identification number of bulls in proximity was noted. The proximity event stopped when one of the bulls moved 1 body length away. The output of the behavior observation obtained by the software contained the identification of the focal subject, the identification of the individual or individuals the focal subject was in proximity with, and the starting and stopping time of the proximity event.

## Validation Analysis

The video observations were considered the gold standard to which the proximity loggers were compared. For this, each second of video observation was compared to the corresponding second recorded or not by the proximity logger, creating confusion matrices for each bull considering every possible dyadic encounter of the focal bull with all bulls wearing collars or between the focal bull wearing collar and all bulls wearing ear tags within its pen.

The second in which the proximity was observed in the video, perceived by the proximity logger, and had bulls' identification matched was considered a true positive (TP). The seconds in which the proximity was neither observed in the video nor perceived by the logger was considered a true negative (TN). The seconds a proximity event was observed in the video but not perceived by the proximity logger was considered a false negative (FN). The seconds in which the proximity was not observed in the video but was perceived by the proximity logger were considered a false positive (FP). If a proximity event was observed in the video and perceived by the collar, but the bulls' identification did not match, an FN was assigned to the dyadic encounter observed in the video, and an FP was assigned to the dyadic encounter perceived by the collar. Sensitivity (Eq. 1), specificity (Eq. 2), precision (Eq. 3), and accuracy (Eq. 4)

**Table 1.** Total time and time per focal bull in which a proximity event was observed in the video, recorded by proximity loggers (collars operating as receiver and transmitter) during corresponding video time, and recorded by logger during the entire period (14 days) of experiment 1 in 12 bulls equipped with proximity logger in 2021

| Proximity events | Time per focal bull (mean ± SD), s | Total time, s |
|---|---|---|
| Observed in video | 5,414 ± 2,887 | 64,817 |
| Recorded by loggers during corresponding video time | 896 ± 976 | 10,752 |
| Recorded by logger during the entire experiment | 103,515 ± 37,747 | 1,242,180 |

were calculated for each focal bull and for the total amount of observations as follows:

$$Sensitivity = \frac{TP}{TP + FN} \quad (1)$$

$$Specificty = \frac{TN}{TN + FP} \quad (2)$$

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

Median and 95% confidence interval (95% CI) were calculated for each metric for both studies. The 95% CI of these metrics were obtained by bootstrapping with 1000 simulation iterations, generating data-based confidence intervals (Greiner and Gardner, 2000) using the '*boot*' package in RStudio (Version 4.3.2, RStudio, Inc.). Outlier values were detected using the interquartile range (IQR) method (Dash et al., 2023). For this, the IQR was calculated (75$^{th}$ percentile to 25$^{th}$ percentile), and any value higher or lower than $1.5 \times IQR$ was considered an outlier. Results with and without outliers were reported. Outlier detection was implemented not only to detect devices with potential malfunctioning but also to reduce the impact of potential biases on proximity detection by the observer. Although visual observations are the current gold standard method to detect proximity among animals, they are not error-free, and factors such as camera position and the distance between the observer and the focal animal may affect the accuracy of the video observations (Hughey et al., 2018).

In devices operating properly as both transmitters and receivers and interacting with each other, it is expected that the duration of events recorded by one receiver will be similar to the one recorded by the other, showing that both transmitters and receivers are operating as expected (Watson-Haigh et al., 2012). As the collars work as both transmitters and receivers, the reciprocity or reciprocal agreement between collars can be assessed as an indirect measure of devices' reliability (Drewe et al., 2012; Watson-Haigh et al., 2012). Thus, reciprocity can be assessed by comparing the duration of dyadic encounters registered by each receiver in pairs of collars (i.e. duration of receiver A perceiving transmitter B vs. duration of receiver B perceiving transmitter A) (Watson-Haigh et al., 2012). To assess the reciprocal agreement between the duration of proximity events observed between each dyad of collars, the concordance correlation coefficient (CCC), bias correction factor, scale shift, and location shift (Lin, 1989) were calculated using the '*epiR'* package in RStudio (Version 4.3.2 (2023-10-31), RStudio, Inc.). Coefficient values were considered negligible (< 0.30), low (0.30 to 0.50), moderate (0.50 to 0.70), high (0.70 to 0.90), or very high (> 0.90) (Hinkle et al., 2003).

The CCC measures the degree of concordance between two variables (in this case, the duration of dyadic encounters recorded by each collar in pairs of collars of Exp. 1) by combining precision (Pearson correlation) and accuracy (bias correction factor) assessments in a coefficient ranging from −1 (perfect reversed concordance) to +1 (perfect agreement) (Lin, 1989). The bias correction factor measures how far the best-fit line deviates from a perfect agreement line (45° line), ranging from 0 to 1, where values closer to 1 indicate smaller deviations (Lin, 1989). The scale shift refers to the differences in the dispersion of the two variables, and values closer to 1 indicate that the variances of the variables are similar (Lin, 1989). The location shift refers to the differences in the means of the two variables while accounting for their variances, and values closer to 0 indicate similar means (Lin, 1989).

## Results

### Experiment 1

All animals in both experiments appeared to be comfortable wearing the collars, with no apparent abnormal behavior within one hour after deployment. A total of 128,430s (35h 40min 30s) of visual observations were obtained from videos recorded in 2021 of 12 bulls, with 10,702 ± 232s (mean ± SD) of visual observation per focal bull. The average duration of a receiver perceiving a transmitter during the entire period was 9,410 ± 7,597s per dyadic encounter (522s to 43,216s). A description of proximity events by video and recorded by the proximity loggers (collars operating as receiver and transmitter) is detailed in Table 1.

Most of the seconds computed from the total amount of observations were assigned as true negatives (1,343,938s, or 95.13%), followed by false negatives (58,040s, or 4.11%), true positives (9,881s, or 0.70%), and false positives (871s, or 0.06%). The metrics calculated from the total amount of observations showed a sensitivity of 0.15, specificity of 1.00, precision of 0.92, and accuracy of 0.96. When these metrics were calculated per focal bull considering all collars, the sensitivity median was 0.10 (95% CI = 0.06 to 0.21), specificity median 1.00 (1.00 to 1.00), precision median 1.00 (0.72 to 1.00), and accuracy median 0.96 (0.95 to 0.97). The precision of Collar ID 3 and Collar ID 7 were detected as outlier values. When these values were removed, the precision median continued 1.00, but the 95% CI increased to 0.97 to 1.00. Table 2 shows the metrics calculated per focal bull and the absolute and relative numbers of true positives, false positives, false negatives, and true negatives used to calculate the metrics.

**Table 2.** Absolute and relative values of true positives, false positives, false negatives, true negatives, sensitivity, specificity, precision, and accuracy of proximity loggers recording proximity events to other collars when compared to visual observations per focal bull (Collar ID), among 12 bulls enrolled in the study in 2021

| Collar ID | True positives | | False positives | | False negatives | | True negatives | | Sensitivity | Specificity | Precision | Accuracy |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Seconds | % | Seconds | % | Seconds | % | Seconds | % | | | | |
| 1 | 3,327 | 2.82 | 0 | 0 | 4,163 | 3.53 | 110,331 | 93.64 | 0.44 | 1.00 | 1.00 | 0.96 |
| 2 | 40 | 0.03 | 0 | 0 | 6,454 | 5.48 | 111,305 | 94.49 | 0.01 | 1.00 | 1.00 | 0.95 |
| 3 | 26 | 0.02 | 11 | 0.01 | 2,859 | 2.43 | 114,562 | 97.53 | 0.01 | 1.00 | 0.70[1] | 0.98 |
| 4 | 710 | 0.62 | 0 | 0 | 3,521 | 3.06 | 110,774 | 96.32 | 0.17 | 1.00 | 1.00 | 0.97 |
| 5 | 1,294 | 1.09 | 19 | 0.02 | 3,372 | 2.84 | 114,016 | 96.05 | 0.28 | 1.00 | 0.99 | 0.97 |
| 6 | 307 | 0.25 | 7 | 0.01 | 4,329 | 3.48 | 119,745 | 96.27 | 0.07 | 1.00 | 0.98 | 0.96 |
| 7 | 71 | 0.06 | 825 | 0.72 | 3,371 | 2.93 | 110,936 | 96.30 | 0.02 | 0.99 | 0.08[1] | 0.96 |
| 8 | 842 | 0.73 | 0 | 0 | 2,891 | 2.50 | 111,965 | 96.77 | 0.23 | 1.00 | 1.00 | 0.98 |
| 9 | 1,883 | 1.59 | 0 | 0 | 10,502 | 8.89 | 105,744 | 89.52 | 0.15 | 1.00 | 1.00 | 0.91 |
| 10 | 5 | 0.004 | 0 | 0 | 740 | 0.62 | 118,132 | 99.37 | 0.01 | 1.00 | 1.00 | 0.99 |
| 11 | 1,283 | 1.12 | 0 | 0 | 8,556 | 7.48 | 104,583 | 91.40 | 0.13 | 1.00 | 1.00 | 0.93 |
| 12 | 93 | 0.08 | 9 | 0.01 | 7,282 | 6.11 | 111,845 | 93.81 | 0.01 | 1.00 | 0.91 | 0.94 |

[1]Values considered outliers by the Interquartile Range method.

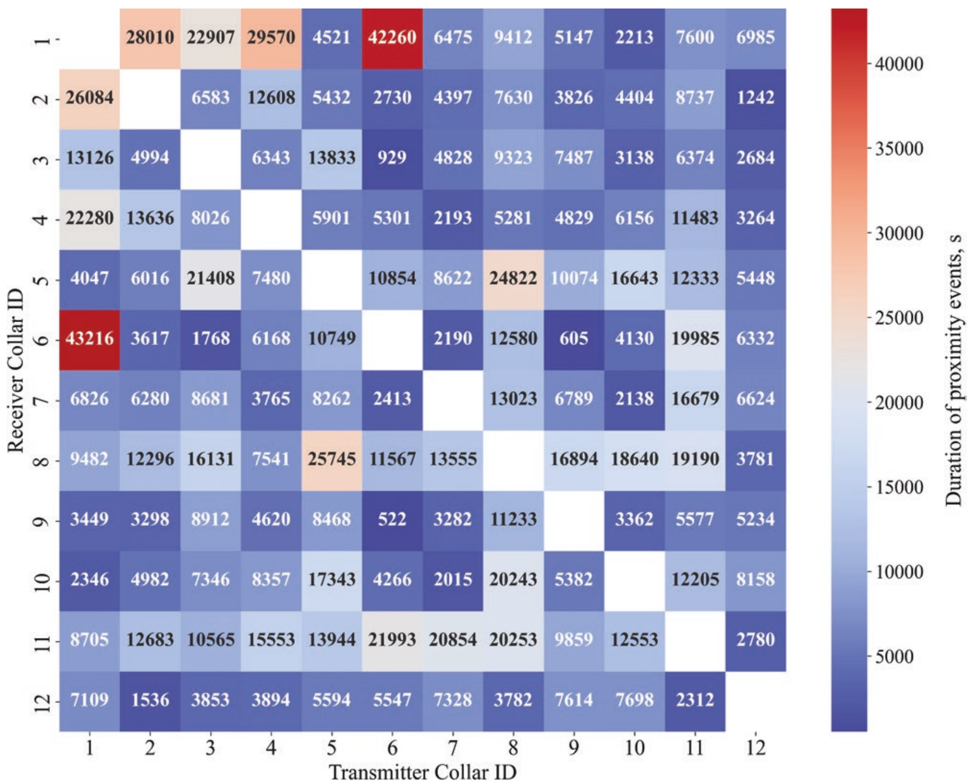


**Figure 1.** Heatmap of the total duration (s) of proximity events recorded by each dyad of the 12 bulls equipped with proximity loggers in experiment 1 (collar-to-collar proximity logger system). All collars in experiment 1 operate as both receivers and transmitters. The dyadic encounters duration (values inside the boxes) represents the number of seconds each receiver perceived each transmitter.

The reciprocity analysis, based on the reciprocal agreement of proximity duration between dyads of collars (Figure 1), showed a very high agreement of 0.93 with a 95% CI coefficient between high and very high (0.89 to 0.96). The scale shift was 0.97, the location shift was 0.09, and the bias correction factor was 0.99. A heatmap of durations of proximity events recorded by each dyad of receiver and transmitter over the entire period of Exp. 1 is presented in Figure 1.

## Experiment 2

A total of 360,493s (100h 08min 13s) of visual observations were obtained from videos recorded in 2023 of 11 bulls, with

**Table 3.** Total time and time per focal bull in which a proximity event was observed by video, recorded by proximity loggers (collars operating as a receiver and ear tags operating as a transmitter) during corresponding video time, and recorded by loggers during the entire period (13 days) of experiment 2 of 11 bulls in 2023

| Proximity events | Time per focal bull (mean ± SD), s | Total time, s |
|---|---|---|
| Observed in video | 14,465 ± 12,748 | 72,323 |
| Recorded by loggers during corresponding video time | 5,075 ± 2,310 | 25,379 |
| Recorded by logger during the entire experiment | 120,265 ± 45,678 | 601,326 |

**Table 4.** Absolute and relative values of true positives, false positives, false negatives, true negatives, sensitivity, specificity, precision, and accuracy of proximity loggers recording proximity events between collars (receivers) and ear tags (transmitters) when compared to visual observations per focal bull-wearing a collar (Collar ID) among the five bulls wearing a collar and five wearing an ear-tag enrolled in the study in 2023

| Collar ID | True positives | | False positives | | False negatives | | True negatives | | Sensitivity | Specificity | Precision | Accuracy |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Seconds | % | Seconds | % | Seconds | % | Seconds | % | | | | |
| 1 | 1,736 | 2.73 | 207 | 0.33 | 3,230 | 5.09 | 58,328 | 91.85 | 0.35 | 1.00 | 0.89 | 0.95 |
| 2 | 3,344 | 2.51 | 316 | 0.24 | 7,424 | 5.57 | 122,265 | 91.69 | 0.31 | 1.00 | 0.91 | 0.94 |
| 3 | 7,409 | 7.97 | 491 | 0.53 | 2,940 | 3.16 | 82,078 | 88.33 | 0.72 | 0.99 | 0.94 | 0.96 |
| 4 | 5,404 | 5.45 | 716 | 0.72 | 3,942 | 3.97 | 89,170 | 89.86 | 0.58 | 0.99 | 0.88 | 0.95 |
| 5 | 4,174 | 3.57 | 1,582 | 1.35 | 32,720 | 28.00 | 78,369 | 67.07 | 0.11 | 0.98 | 0.73[1] | 0.71[1] |

[1]Values considered outliers by the interquartile range method.
[2]Only the results of bulls wearing a collar are displayed because the collars are the receivers, registering all data transmitted from the ear tags. As ear tags do not operate as receivers, they don't record any data.

32,772 ± 4,335s (mean ± SD) of visual observation per focal bull. Proximity events between focal bulls wearing collars with loggers activated (receivers detecting ear tag transmitters) and one or more bulls wearing the ear tag transmitters recorded in video and by devices are detailed in Table 3. All animals appeared comfortable wearing the collars and ear tags, with no apparent abnormal behavior within less than one hour after deployment.

Most of the seconds computed from the total amount of observations were assigned as true negatives (430,210s, or 85.05%), followed by false negatives (50,256s, or 9.94%), true positives (22,067s, or 4.36%), and false positives (3,312s, or 0.65%). The metrics calculated from the total amount of observation showed a sensitivity of 0.31, specificity of 0.99, precision of 0.87, and accuracy of 0.89. When these metrics were calculated per focal bull wearing a receiver collar, the sensitivity median was 0.35 (95% CI = 0.24 to 0.61), specificity 0.99 (0.99 to 1.00), precision 0.89 (0.80 to 0.92), and accuracy 0.95 (0.81 to 0.95). The precision and accuracy of Collar ID 5 were detected as outlier values. When these values were removed the precision increased to 0.90 (0.88 to 0.93) and accuracy to 0.95 (0.94 to 0.96). Table 4 shows the metrics calculated per focal bull and the absolute and relative numbers of true positives, false positives, false negatives, and true negatives used to calculate the metrics.

## Discussion

Overall, similar results were observed in both experiments, where both collar-to-collar (experiment 1) and collar-to-ear tag (experiment 2) proximity loggers systems presented high precision, specificity, and accuracy (> 0.89), but low sensitivity (< 0.35) before and after outliers were removed. These results showed that most of the observations detected by the observer will not be perceived by the logger due to its low sensitivity, but those perceived are highly reliable due to its high precision. These results are aligned with previous studies investigating different transmitter power rates (in horses, deer, and calves), which observed that at lower transmitter power, sensitivity was lower than specificity and precision (Ossi et al., 2022; Ben Meir et al., 2023).

The transmitter power is one of the most important parameters to influence not only the sensitivity and precision of proximity loggers but also the battery lifespan of devices and should be carefully aligned with the purpose of the study (Triguero-Ocaña et al., 2019). Higher transmitter power (closer to L1 in the Lotek LiteTrack LR collars or Lotek V7E 154D ear tag) is likely to lead to higher sensitivity but also more false positives (i.e., lower precision) due to the signal reaching further and being potentially perceived outside the pre-set range (Ossi et al., 2022). The increase in transmitter power will also lead to a shorter battery lifespan (Triguero-Ocaña et al., 2019). Beef bulls are usually managed extensively, especially while in breeding pastures, and it is not possible to handle them so often to change or recharge batteries. Therefore, a compromise in sensitivity to prolong the battery lifespan while recording highly reliable data (high precision) for long periods is a reasonable setting for many studies investigating beef bull behavior.

The inter-logging variation was identified as a potential issue for using proximity loggers in the past because, within a group of devices, some might be more sensitive than others, leading to lower reciprocity (Boyland et al., 2013). In this study, although a variation in sensitivity was observed (Exp. 1: 95% CI = 0.06 to 0.21; Exp. 2: 95% CI = 0.24 to 0.61), no outlier values of sensitivity were detected. On the other hand, the precision of two collars in Experiment 1 and the precision and accuracy of one collar in Experiment 2 were considered outliers. However, when assessing the reciprocity as an indirect measure of reliability in Experiment 1, a very high agreement was observed in addition to a high scale shift and bias correction factor and low location shift, indicating high reciprocal agreement (Watson-Haigh et al., 2012). These discrepancies, such as the elevated number of false positives of specific collars (e.g., Collar ID 7 in Exp. 1 = 2.93%, and Collar ID 5 in Exp. 2 = 28%) and precision outliers, might be explained by the interaction of environmental elements with the radio signal that leads to propagation impairment phenomena occurring during the visual observation (Watson-Haigh et al., 2012; Triguero-Ocaña et al., 2019).

In the case of Collar ID 7 in Experiment 1 (lowest precision), for example, approximately 30% of its visual observations were recorded on a rainy day in which he was close to a windbreaker (structure of metal and wood) which might have caused interferences with the signal propagation and impacted its precision. However, this was not reflected in its reciprocal agreement and in the heatmap of dyadic encounter durations over the entire experimental period, showing no significant discrepancies between receivers and transmitters. In addition, it is known that although visual observation is still the gold standard for behavioral observations, there are multiple aspects that can bias its measurements (Hughey et al., 2018), which might also impact the results. Nonetheless, as the impact of environmental and observer factors on the reliability of loggers is out of the scope of this study, it was not directly investigated.

Although the use of proximity loggers provides multiple benefits over visual observation in the study of social interactions, such as mitigation of the bias caused by the presence of an observer (Allan et al., 2022) and monitoring several animals uninterruptedly for long periods (Ryder et al., 2012), it can increase the cost of the data collection (Ryder et al., 2012). The collars used in this study cost approximately ten times more than the ear tags, which might be prohibitive for some researchers or commercial operations. However, for some applications, such as interactions between bulls and cows (O'Neill et al., 2014), the system presented in Experiment 2 might be a solution. Using ear tags in most animals and collars in a few key individuals (e.g., ear tags in cows and collars in bulls within a breeding group) will reduce the costs with equipment, and proximity events will be recorded in quantity and with the quality needed for social behavioral studies (Ryder et al., 2012). It is important to mention that the ear tags used in this study do not store any data and operate only as transmitters. Therefore, in the scenario mentioned above, no proximity among animals wearing ear tags will be recorded, and all data will be stored in the collars. When interested in recording proximity among all individuals in a group, the system described in Experiment 1 should be used.

Another limitation of using proximity loggers to study social behaviors, assumed by previous studies, is the inability to differentiate the type of interaction (Ryder et al., 2012), leading to inferences of social interactions based on spatial proximity among individuals (Castles et al., 2014). However, more recent reports have shown promising results in differentiating affiliative interactions from agonistics based on the duration of proximity events of Holstein calves (Ben Meir et al., 2023). Such differentiation could be further investigated using both systems tested in this study as the results indicated that both loggers quantified proximity events and the duration of these events. Additionally, the ability to record events among several individuals, demonstrated by the heatmap of dyadic encounter durations from Exp. 1, can address the challenge of recording interactions within a herd (Hubbard et al., 2021). This approach has potential applications for social dominance ranking in beef bulls and the relationship between different aspects of social behavior with their reproductive success.

Finally, it is important to mention that the low sensitivity observed in both proximity logger systems might be a concern for studies in which the contact rate is the measure of interest, such as those modeling disease spread. For those studies, devices with high transmitter power should be chosen. Furthermore, it is possible that environmental elements (e.g., air humidity, distance from structures with different materials and densities, etc.) have interfered with the propagation of the signal, but limited inferences can be made about it as the study was not designed to proper investigate these effects. Although we acknowledge the potential limitation of this study regarding its sample size (especially in experiment 2), previous studies have validated proximity loggers using the same sample sizes (Triguero-Ocaña et al., 2019) or smaller and observed similar results whether using 2 or 4 animals (Ossi et al., 2022). As one of the less studied sensors in precision livestock monitoring research (Besler et al., 2024), many aspects of proximity logger use in cattle remain unexplored. Future studies should investigate the effect of environmental elements on the sensitivity and precision of these devices in a large group, as well as how changes in transmitter power and RSSI threshold interact with battery discharge rate, precision, and sensitivity in both systems.

## Conclusion

The Lotek LiteTrack LR collars with built-in proximity loggers can record proximity events within 2.5 to 3m of other collars or to the Lotek V7E 154D ear tags with high precision but low sensitivity. Furthermore, the collars presented a high reciprocal agreement, an indirect indicative of devices' reliability. This study provides the first validity estimates of these two proximity logger systems in recording proximity events among beef bulls and provides knowledge for researchers to utilize remote monitoring technology in the field for better evaluating cattle behavior in remote settings

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## Conflict of Interest Statement

The authors declare no real or perceived conflicts of interest.

## Author Contributions

Vinicius Camargo (Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing—original draft, Writing—review & editing), Ed Pajor (Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Resources, Supervision, Writing—review & editing), and Jennifer Pearson (Conceptualization, Formal analysis, Funding acquisition, Investigation, Project administration, Resources, Supervision, Writing—review & editing)

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