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Virtual fencing in remote boreal forests: performance of commercially available GPS collars for free-ranging cattle

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Abstract

Background The use of virtual fencing in cattle farming is beneficial due to its flexibility, not fragmenting the landscape or restricting access like physical fences. Using GPS (Global Positioning System) technology, virtual fence units emit an audible signal and a low-energy electric shock when crossing a predefined border. In large remote grazing areas and complex terrains, where the performance of the GPS units can be affected by landscape structure, increased positioning errors can lead to unnecessary shocks to the animals leading to animal welfare concerns. This study aimed to explore factors affecting the GPS performance of commercially available virtual fence collars for cattle (NoFence©), both using static tests and mobile tests, i.e., when deployed on free-ranging cattle.

Results The static tests revealed generally high fix success rates (% successful positioning attempts), and a lower success rate at four of 30 test locations was most likely due to a lack in GSM (Global System for Mobile communications) coverage. On average the GPS precision and accuracy errors were 3.3 m ± 2.5 SD and 4.6 m ± 3.2 SD, respectively. We found strong evidence that the GPS precision and accuracy errors increased errors under closed canopies. We also found evidence for an effect of the sky-view on the GPS performance, although at a lesser extent than canopy. The direction of the accuracy error in the Cartesian plane was not uniform, but biased, depending on the aspect of the test locations. With an average of 10.8 m ± 6.8 SD, the accuracy error of the mobile tests was more than double that of the static tests. Furthermore, we found evidence that more rugged landscapes resulted in higher GPS accuracy errors. However, the error from mobile tests was not affected by canopy cover, sky-view, or cattle behaviors.

Conclusions This study showed that GPS performance can be negatively affected by landscape complexity, such as increased ruggedness and covered habitats, resulting in reduced virtual fence effectiveness and potential welfare concerns for cattle. These issues can be mitigated through proper pasture planning, such as avoiding rugged areas for the virtual fence border.

Keywords Virtual fencing, Cattle farming, Free-ranging cattle, GPS performance, GPS errors, Grazing management, Animal welfare, Boreal forests

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Background

In recent decades the use of Global Positioning System (GPS) tags to study animal movement and behavior remotely has become the gold standard [1–4]. Various fields within ecology are using GPS technology to understand animal movement dynamics, such as migration, habitat use, social interactions, constraints to movement, and behavior [5–8]. With improved battery life, smart attachment systems, and low production costs, the research potential has broadened [1, 4, 9]. Additionally, with the continued emergence of novel applications for livestock, GPS tags are now also available for livestock farmers [1, 10]. The use of sensors to remotely monitor livestock has mostly been developed for indoor and pasture management with the aim to improve production efficiency and animal welfare [1].

A new advance in livestock farming is the application of virtual fencing. Contrary to physical fences, virtual fences do not fragment the landscape for other than the target individuals, restrict human access, reduce wildlife movement nor cause injuries [10–12]. The pasture limited by the virtual fence is contained as a digital polygon in tags attached to the animals. When an animal crosses the virtual fence, as determined by the GPS unit in the tag, the tag emits an audible signal followed by a subsequent low-energy electric impulse (0.2 J, 3 kV, 1.0 s) (hereafter called electric shock). By conditioning the animal to the acoustic stimulus, it will learn to stop and turn around before it receives the electric shock [13]. The use of an antecedent stimulus in combination with the consequential electric shock if the movement trajectory is unaltered is similar to that of a physical electric fence (visual stimulus). However, there are concerns about animal welfare as there is still limiting information about how different species, breeds and individuals respond to the acoustic cue and the electric shock [14–16]. Several European countries, such as Denmark and Sweden, have so far banned the use of collars using electric shocks [11, 14, 16].

Virtual fence systems are implemented on pastures and are also applied by farmers and ranchers who practice free-ranging grazing in more remote and forested or alpine areas, such as in Scandinavia [17], North America [18], and Australia [19] where free-ranging livestock grazing has a long tradition. Using virtual fence collars reduces the costs of setting up and maintaining physical fences in difficult terrain [10], avoids conflicts with other landowners and stakeholders by excluding areas where the cattle should not graze, and improves the monitoring potential for animal welfare concerns. However, in large and topographically complex landscapes, the precision and accuracy of the GPS unit used to estimate the distance of the animal to the virtual fence might be impacted. This can result in welfare issues when individuals are roaming close to the fence. An error in GPS positioning can suddenly lead to emission of the acoustic stimulus followed by an electric shock, even though the animal is within the boundary of the virtual fence. Getting unclear warning sounds and shocks can confuse and stress the animal. Thus, quantifying the influence of landscape structure on virtual fence performance is critical to avoid unnecessary electric impulses, i.e., an individual must have the choice to turn around to avoid an impulse [10, 11, 20].

Previous studies found that factors describing the landscape structure, such as elevation, sky-view, slope, aspect, and canopy cover can potentially affect the precision and accuracy errors of GPS units [21–24]. More openness in the landscape, such as at higher elevations, more available sky, and open vegetation structures result in better fix rates, and less GPS precision errors and GPS accuracy errors [21–24]. However, most studies on GPS performance use stationary units, not attached to an animal of the target species. Those studies that tested GPS performance on deployed GPS units found larger errors in GPS accuracy then in stationary tests of the same units [25, 26]. Lower performance of deployed GPS units might be due to sub-optimal placement of the GPS antenna (when the animal body blocking parts of the GPS antenna's receiving range) [27–29], vegetation structure and cover [23, 26, 29], and animal behavior and activity patterns [30, 31].

While GPS technology used to monitor and study animals continues to undergo rapid development and refinement, the importance of understanding and gaining insight into the performance of the GPS units is still essential [24]. Therefore, providing more insight about factors affecting the performance of GPS units is meaningful for farmers to design their grazing areas, for authorities to decide about approval of virtual fencing systems, and for scientists by providing fundamental information for habitat use and resource selection studies [23, 25].

In this study, we explored factors affecting the fix success rate, GPS precision error, and GPS accuracy error of NoFence©'s collars, commercially available virtual fence collars for cattle. Our tests were conducted on both static collars and those deployed on free-ranging cattle in mobile tests. We expected that elevation and sky-view would positively impact the GPS precision errors and the GPS accuracy errors while slope, canopy cover, and terrain ruggedness would have a negative effect. We also expected to find higher rates of GPS accuracy error when the collars were mounted on the cattle, compared to the static tests, as the cattle's body might obstruct the GPS. Furthermore, we explored if the aspect of the collar's location affected the GPS accuracy error. We expected that the hill's aspect would result in directional deviations from the true location, due to the hill's potential of shading satellites.

Methods

Study area

Our study was conducted in the boreal forest of south-eastern Norway on two grazing areas of each up to 25 km^2 (Fig. 1). The areas were dominated by forest and consisted of a mosaic of pine and spruce forest stands of different ages intermixed with bogs. The elevation ranged from 235 to 680 m with an average elevation of 368 m, slopes were between 0 to 65 degrees with an average of 6 degrees, and the sky-view was 0.94 on average and ranged from 0.41 to 1.00 across the grazing areas. The ruggedness of the areas, i.e., the change in elevation relative to the direct surrounding [32], was low with an average terrain ruggedness index of 5 (range = 0–103). The areas were accessible by gravel roads with occasional traffic. The same farmer utilized both areas for beef cattle grazing throughout the summer months, approximately from the end of May until beginning of September, annually. In the year of this study, 2022, the farmer released 18 and 23 Hereford beef cows (average age: 4 years, range: 2–7 years) with their suckling calves on the eastern and western grazing area, respectively (Fig. 1).

NoFence collars

The farmer equipped all adult beef cows with NoFence© virtual fence collars (models C2, C2.1, and C2.2). The collars registered GPS positions at 5-min intervals, and in addition they registered every warning or electric shock event when cattle crossed the virtual boundary. The cattle were accustomed to the collars through a learning period at the farm, following the guidelines provided by NoFence© [33].

Static tests

Static tests implied measuring GPS precision and accuracy errors when the collars were deployed at stationary locations (hereafter stations) for 24 h and acquiring positions at 5-min intervals. We used four collars during one session and rotated them through all stations for 2 weeks starting on the 8th of August 2022 until 20th of August 2022. During normal functioning, the collars would turn off the GPS unit if an animal was stationary to reduce battery usage. For the static tests NoFence© deactivated this automated turn off function to enable continuous collection of GPS positions. We selected 32 stations, half of which were placed in open habitat and the other half in closed canopy (0% and > 80% canopy cover, respectively), yet the data were only collected at 30 stations because of collar failure. Furthermore, the stations followed eight

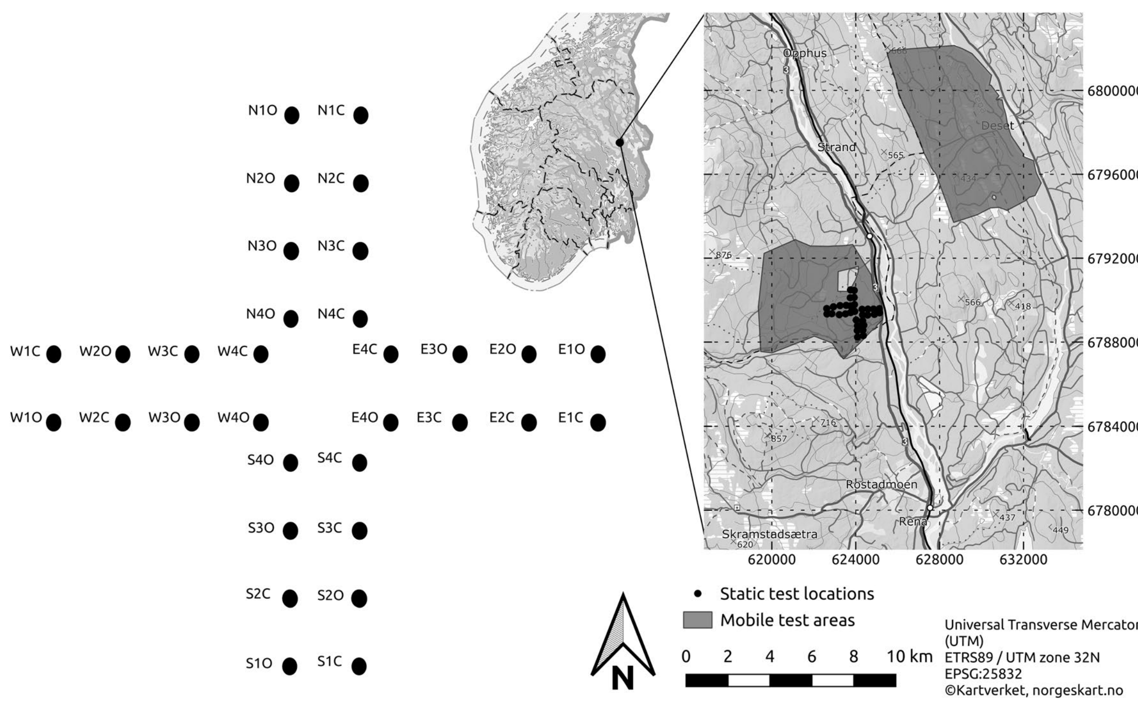

Fig. 1 Overview of the locations for the static tests. Including the schematic overview of the study design: the first letter indicates the slope's cardinal direction, the number corresponds to an increased elevation level (1 low—4 high), and 'O' or 'C' stands for open or closed habitat, respectively. The map indicates the locations of the static tests (black dots) and the areas for the mobile tests (darkened shapes). The study area is located north of the village Rena in south-eastern Norway

elevational gradients (ranging from 240 to 455 m), with two gradients per aspect category (N, E, S, W facing slopes) (Fig. 1). We hung the collars about 20 cm above the ground using bamboo tripods (Fig. 2). The true position was measured with a differential GPS (Emlid Reach RS2+, Emlid Tech Ltd.). Furthermore, at each station the crown cover was measured in percentage by using the HabitApp [34] on a Samsung Galaxy Tablet.

Mobile test

The mobile tests were performed from the 6th to the 22nd of July 2022 by observing the cattle and measuring their locations with a differential GPS (Emlid Reach RS2+, Emlid Tech Ltd.). The cattle were approached after locating their positions using the NoFence© App. Field personnel approached the herd from an open area, such as young forest stands, roads, and forest paths, as this decreased the risk of scaring off the herd. The cattle were identified by reading their ear-tag numbers, their body position was registered (standing or laying) and a reference picture was taken so their exact location could be clarified later. Only the cattle that were stationary for at least 5 min were included in the test, to ensure that a new GPS position was taken. After the cattle had left the area, the field personnel visited the cattle locations, guided by the pictures as mentioned above, and measured the cattle's locations with the differential GPS. At each location, the crown cover was measured with the HabitApp [34] analogous to the static tests.

Environmental variables

We used QGIS version 3.34.4 [35] to obtain rasters for the elevation (meters), slope (degrees), aspect (bearing degrees), terrain ruggedness index, and sky-view using a Digital Elevation Model with a 10-m resolution (©Kartverket, hoydedata.no). Sky-view was calculated using a radius of 500 m around each pixel (radius of 50 pixels) on a scale from 0 to 1 (no sky-view, 100% available sky, respectively) [36]. Thereafter, we sampled each GPS position using R version 4.4.1 [37] within the interface of Rstudio version 2023.12.1.402 [38] by using the function 'extract' from the package 'terra' [39].

Fig. 2 Placement of static collars in **A** open habitat and **B** closed habitat. Photos by Sarah Gaunet

Analyses

We calculated the fix success rate by counting the recorded fixes across 24 h and dividing this count by 289 (total number of fix acquisitions, 12 fixes per hour for 24 h, including the first fix). The GPS acquisition interval was not always exactly 5 min, and when the GPS failed to acquire a position, the time between fixes could be longer than 5 min. Therefore, we calculated the average and range of the time difference between the fixes.

The collars collected the number of satellites and the Horizontal dilution of precision (HDOP) values for each fix. The HDOP values provided by NoFence© had been initially multiplied by 100, so we back transformed these to the standard range of HDOP. The time needed to acquire a fix was not recorded. Furthermore, we defined the GPS precision error by averaging the GPS fixes per station across the 24-h period and calculating the physical distance between each GPS fix and the average location in meters. Similarly, we calculated the GPS accuracy error as the distance in meters between each GPS fix and the true position measured by the differential GPS [40].

We tested for collinearity among predictor variables using the Pearson correlation test, both for the static and mobile tests, and if the correlation coefficient r was < 0.7 or > -0.7, we decided to retain the variable in the models [41]. Thereafter, we ran a linear mixed model (LMM) with the number of satellites as the response variable and predictor variables. Furthermore, we ran generalized linear mixed models (GLMM) with the HDOP value, GPS precision error or GPS accuracy error as the response variable using a gamma distribution with a log-link and station as random intercept (1|station). For the mobile test, we also ran a GLMM using a gamma distribution with a log-link and with GPS accuracy as response variable. We used the function 'glmmTMB' [42] to fit the models. We checked model assumptions using the function 'check_model' [43] and the function 'simulateResiduals' [44]. We described the statistical significance of the results in the language of evidence [45]. Plots were made using the packages 'ggplot2' [46] and 'sjPlot' [47]. We used a wind rose plot to visualize if the GPS accuracy error was deviating towards a specific cardinal direction depending on the aspect category (N, E, S, W) of the station. We described the data spread and range for each aspect category using circular descriptive statistics where we calculated the mean direction (Θ), circular standard deviation (ν), and the circular variance (V_m) [48, 49].

Furthermore, we tested for each cardinal direction if the data followed a uniform distribution using the Watson's goodness of fit test [48, 49]. We assumed that when the data followed the uniform distribution there was no evidence for any directional deviation. The analyses, including data, R-scripts, and model checks are freely available at DataverseNO (see Availability of data and materials).

Results

Collar fix rate

The static collars had on average a GPS fix success rate of 98% (range = 64–100%), with an average of 5.04 min (range = 0–85.60 min) between consecutive fixes indicating that double fixes and large gaps in fixes happened. The GPS fix success rate was almost 100% for all but four stations: S1C (64%), W2C (65%), E3O (96%) and W1C (94%) (Fig. 3). Additionally, one collar failed during the last days of the trial and therefore no data was collected for stations E4C and E1C.

Variable correlations

The variables sky-view, slope, and terrain ruggedness index of the static tests were strongly correlated ($r > 0.8$ or $r < -0.8$) (Additional file 1: Fig. S1A). Furthermore, sky-view and aspect were moderately correlated (Additional file 1: Fig. S2). We included the continuous variables elevation and sky-view, and the categorical variables aspect and canopy cover when modeling number of satellites and GPS precision and accuracy errors for the static tests. However, we tested a model excluding aspect to determine if the potential correlation between sky-view and aspect caused any issues with collinearity. For the mobile test variables, none of the explanatory variables were strongly correlated (Additional file 1: Fig. S1B). Therefore, all the numerical explanatory variables were included in the model together with the categorical variables canopy cover and cattle behavior.

Static collar models

The models included all data for the number of satellites (mean = 17, SD = 2.3, range: 9–23), HDOP value (mean = 0.68, SD = 0.1, range: 0.5–1.96), GPS precision error (mean = 3.3 m, SD = 2.5 m, range: 0.1–86.2), and GPS accuracy error (mean = 4.6 m, SD = 3.2 m, range 0.1–88.2 m). The model for the number of satellites showed strong evidence for an positive effect of sky-view ($P < 0.001$, $\beta = 0.78$, 95% CI [0.49, 1.07]) and elevation ($P = 0.009$, $\beta = 0.34$, 95% CI [0.09, 0.60]) (Fig. 4A). Furthermore, we found strong evidence for an increased number of satellites in open than closed canopy cover ($P = 0.007$, $\beta = 0.63$, 95% CI [0.17, 1.08]) (Fig. 4A). We found evidence for lower number of satellites in the aspect categories South and West than the reference category East ($P = 0.001$, $\beta = -1.28$, 95% CI [−2.04, −0.52], $P = 0.036$, $\beta = -1$, 95% CI [−1.94, −0.06], respectively) (Fig. 4A). A station with a low sky-view (0.8) and closed canopy had on average 3.3 more satellites than a station with a high sky-view (1.0) and open canopy (15.5 ± 0.4 SD, 18.8 ± 0.5 SD, respectively) (Fig. 5A). The model for the HDOP values showed strong evidence for a negative

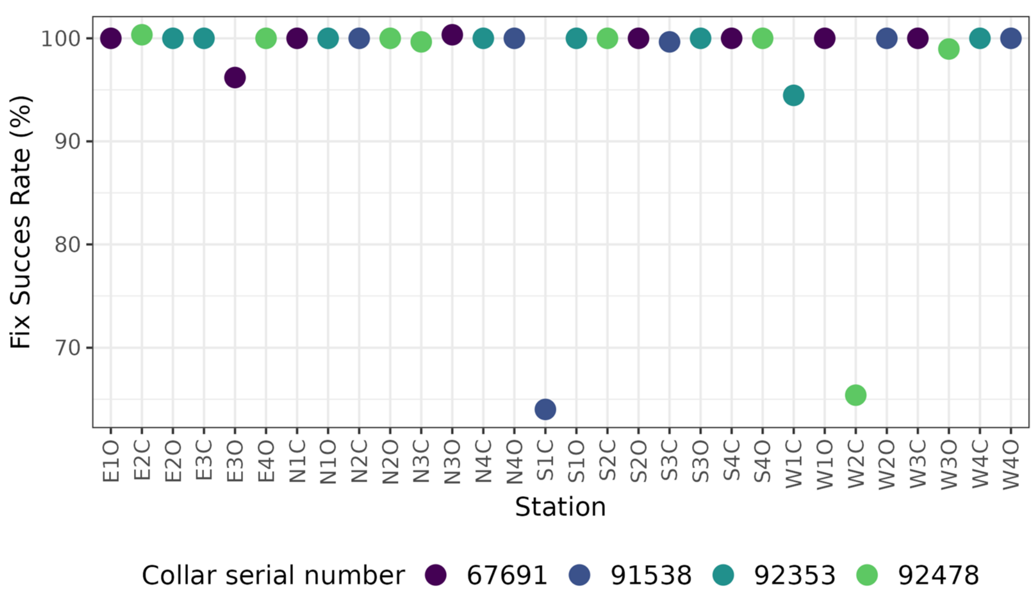

Fig. 3 Fix success rate per station, based on the number of successful GPS fixes by the max potential fixes for 24 h (289 fixes). The colors represent the four different collar's serial numbers used in the experiment. Stations with a fix success rate > 100% indicate a constant positioning interval < 5 min, resulting in one more fix than the estimated number of fix acquisition attempts

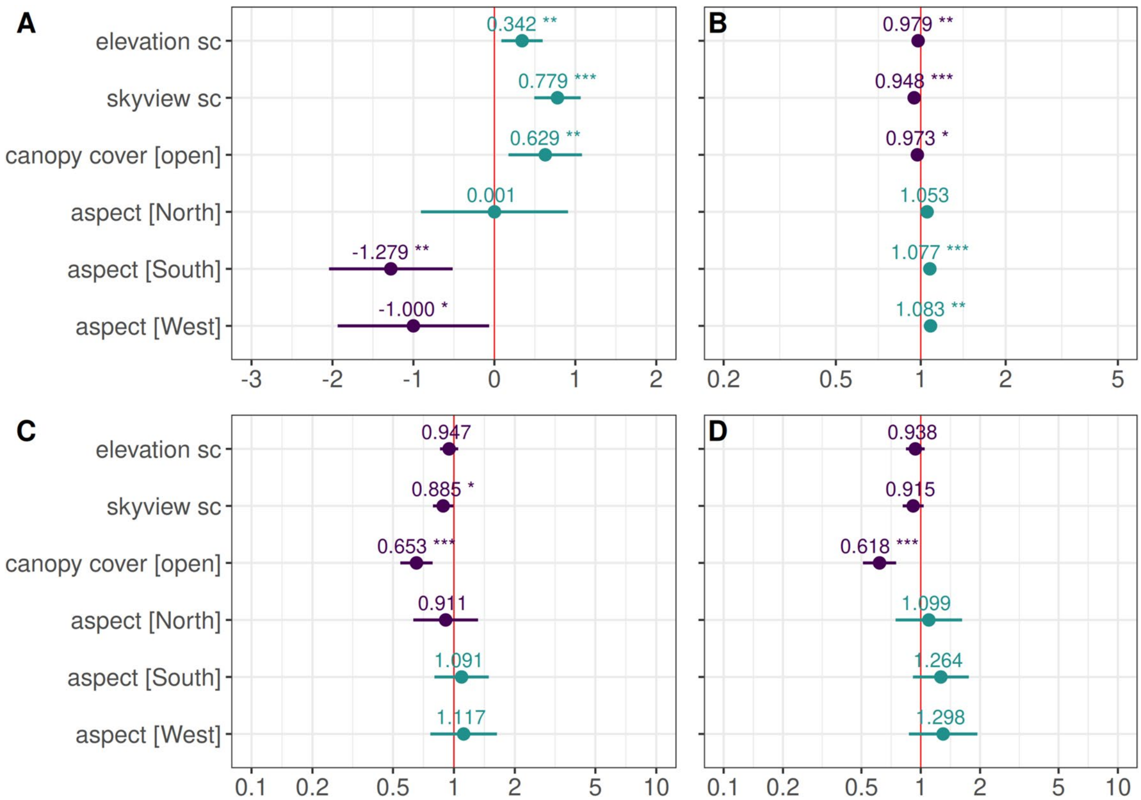

Fig. 4 The model estimates for the static tests including their confidence intervals for **A** the number of satellites LMM model with 17 as reference level (intercept), **B** the HDOP value GLMM model with 0.65 as reference level (intercept), **C** the static GPS precision error GLMM model with 3.872 as reference level (intercept) and **D** the static GPS accuracy error GLMM model with 4.715 as reference level (intercept). The models included scaled numerical explanatory variables (sc), station as random effect, and the GLMM models were modeled on a gamma distribution with a log-link and their estimates were back transformed to the original scale. Purple suggests a negative effect and green a positive effect. Furthermore, abrogated stars indicate the strength of evidence

effect of elevation ($P=0.004$, $\beta=0.98$, 95% CI[0.96, 0.99]) and sky-view ($P<0.001$, $\beta=0.95$, 95% CI[0.93, 0.96]) (Fig. 4B). We found moderate evidence for lower HDOP values in open than closed canopy cover ($P=0.04$, $\beta=0.97$, 95% CI [0.95, 1]) and strong evidence for higher HDOP values for the aspect categories South and West and moderate evidence for the aspect category North than the reference category East ($P<0.001$, $\beta=1.08$, 95% CI [1.03, 1.13], $P=0.004$, $\beta=1.08$, 95% CI [1.03, 1.14], $P=0.05$, $\beta=1.05$, 95% CI [1, 1.1], respectively) (Fig. 4B). From a station with a low sky-view (0.8) and closed canopy to a station with a high sky-view (1.0) and open canopy, the HDOP values decreased with 0.13 (0.72 ± 0.02 SD, 0.59 ± 0.02 SD, respectively) (Fig. 5B).

The model fit for the GPS precision and accuracy error models did not improved by excluding the categorical variable aspect. The model for GPS precision errors showed strong evidence for a lower error for open than closed canopy cover ($P<0.001$, $\beta=0.65$, 95% CI [0.53, 0.79]), moderate evidence for a negative effect of sky-view ($P=0.04$, $\beta=0.88$, 95% CI [0.78, 0.99]), and no evidence for an effect of elevation nor aspect ($P>0.3$) (Fig. 4C). From a station with a low sky-view (0.8) and closed canopy to a station with a high sky-view (1.0) and open canopy, the precision errors decreased with 3 m (5.1 m ± 0.6 SD, 2.1 m ± 0.2 SD, respectively) (Fig. 5C). The model for GPS accuracy errors showed strong evidence for lower errors in open than closed canopy cover ($P<0.001$, $\beta=0.62$, 95% CI [0.51, 0.75]). However, we found little evidence for a negative effect of sky-view ($P=0.16$, $\beta=0.92$, 95% CI [0.81, 1.03]) (Fig. 4D). Furthermore, we found little evidence for an effect of the aspect category South ($P=0.18$, $\beta=1.26$, 95% CI [0.91, 1.75]) and West ($P=0.2$, $\beta=1.30$, 95% CI [0.87, 1.94]) (Fig. 4D). From a station with a low sky-view (0.8) and closed canopy to a station with a high sky-view (1.0) and open canopy, the accuracy error decreased with 3.1 m (5.6 m ± 1.0 SD, 2.5 m ± 0.5 SD, respectively) (Fig. 5D).

Directional deviation

The total number of observations within each aspect category (N, E, S, W) varied from 1150 to 2794

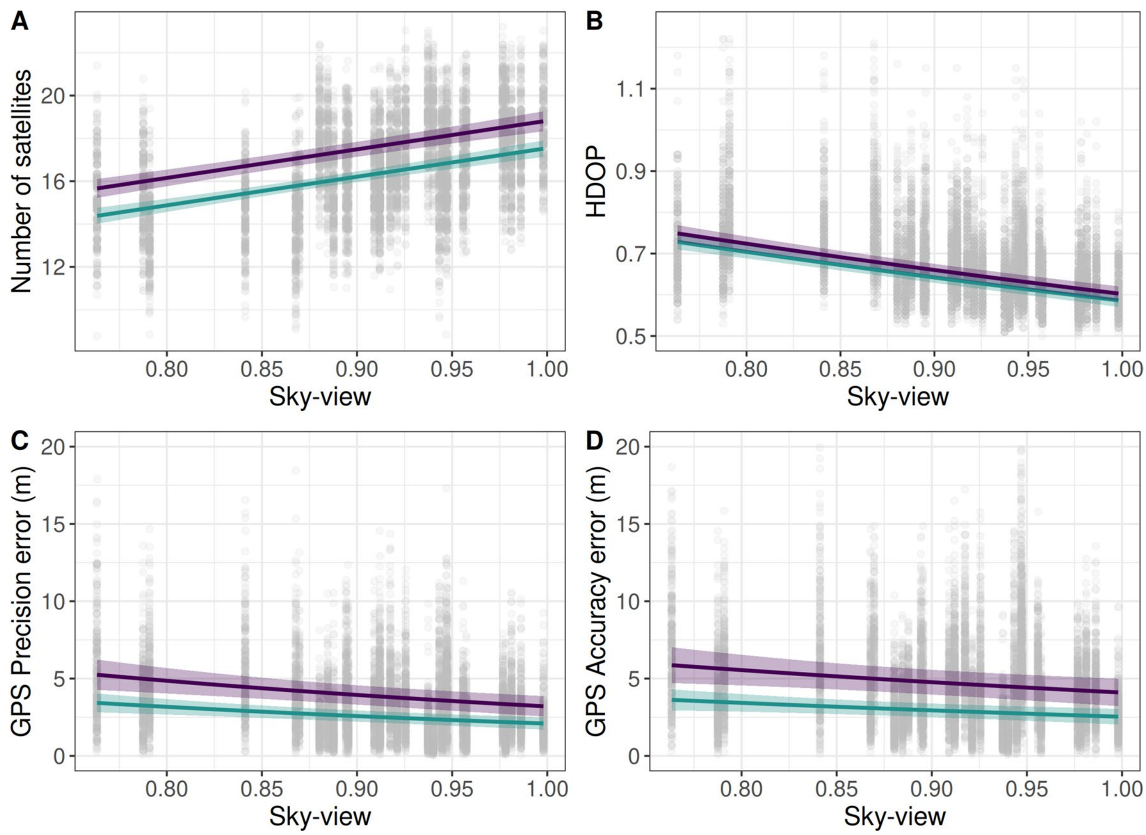

Fig. 5 Prediction plot for the static tests **A** number of satellites, **B** HDOP values, **C** GPS precision errors, and **D** GPS accuracy errors in relation to the sky-view for closed (purple line and ribbon) and open (green line and ribbon) canopy cover. The gray points are the original observations, with HDOP values > 1.25 and GPS errors > 20 m excluded to improve readability (total observations: n = 8466, HDOP: n = 8453, precision error: n = 8461, accuracy error: n = 8458)

observations. The average accuracy errors ranged from 3.9 m on eastern slopes to 5.3 m on southern slopes (Table 1, Fig. 6). None of the aspect categories had a uniform distribution of the directional deviations ($P < 0.01$). The aspect category North showed the largest variation around the mean direction ($\Theta = 24.8° \pm 113.6°$, $V_m = 0.86$), while the category South had the lowest ($\Theta = 255.6° \pm 74.2°$, $V_m = 0.57$) (Table 1, Fig. 6).

Mobile tests

We obtained 92 observations from 32 individual cattle. Each individual was on average observed 2.8 times (range = 1–7) during the data collection period. The eastern and western grazing areas had 40 and 52 observations, respectively. The average accuracy error was 10.8 m (SD = 6.8 m, range = 1.1–34.5). The terrain ruggedness index was the only co-variate with strong evidence ($P = 0.002$, $\beta = 1.28$, 95% CI [1.10, 1.51]) (Fig. 7A) of

Table 1 Descriptive statistics for the accuracy error and circular statistics of the static tests with the average accuracy error (m), range of the accuracy error (m), total observations (N), mean direction (Θ), circular variance (V_m), and circular standard deviation (v) for the four aspect categories (N, E, S, W)

Aspect	Average accuracy error (m)	Range accuracy error (m)	Total N	Mean direction (Θ)	Circular variance (V_m)	Circular standard deviation (v)
North	4.1	0.06 – 17.2	2611	24.8° (NNE)	0.86	113.6°
East	3.85	0.11 – 14.5	1150	176° (S)	0.75	95.9°
South	5.3	0.11 – 88.2	2794	255.6° (W)	0.57	74.2°
West	4.52	0.10 – 24.9	1911	26.5° (NNE)	0.65	82.8°

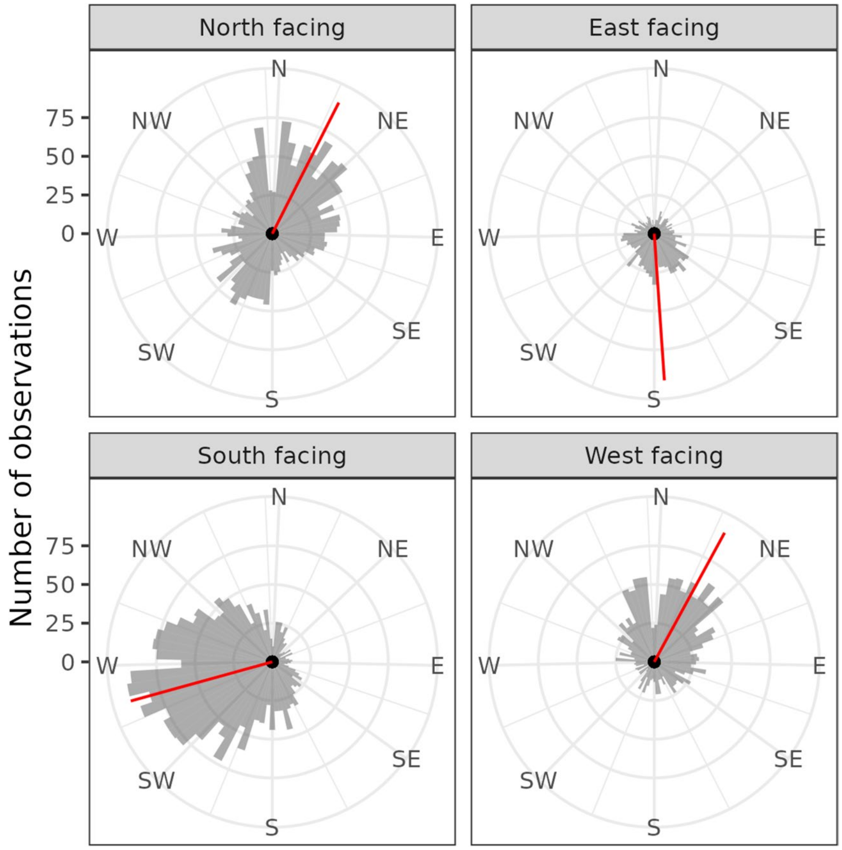

Fig. 6 Wind rose plot for the direction of the accuracy error for each of the aspect categories (N, E, S, W) using the static test data. Increasing gray bars indicate increased number of observation into that specific direction. The red line indicates the mean direction

an effect on the accuracy error. The accuracy error was 2.9 times higher in areas with high (index = 14) compared to low (index = 2) terrain ruggedness (21.5 m ± 6.0 SD, 7.4 m ± 1.0 SD, respectively) (Fig. 7B).

Discussion

Virtual fences for cattle management show tremendous promise due to potential reduced costs for fence maintenance and increased flexibility in management, such as rotational grazing and larger grazing areas. Nevertheless, their usage remains controversial from an animal welfare perspective, partly due to concerns that GPS errors could inadvertently trigger unnecessary stimuli. Our study attempted to quantify these concerns by exploring how environmental factors affect GPS performance of commercially available virtual fence collars in remote boreal forests. We provide optimistic error rates by using fixed stations and contrasted these with errors derived from free-ranging cattle, and contextualize these findings by estimating how typical pasture size would be affected by these errors. Static collars had high fix success rates but nonetheless the GPS precision and accuracy resulted in lower errors in open canopies and precision was positively related with sky-view. For the mobile tests, we found that, on average, the GPS accuracy error was double what was measured in the static tests (10.8 m compared to 4.6 m, respectively).

Fix success rate

Fix success rates were very high except at two stations. Additionally, we found long time gaps between fixes, which can pose problems for both monitoring and research. As well, topography can have considerable effects on GPS performance. Studies in mountainous terrain reported fix success rates below 50% [22, 29], while studies in large relatively flat areas (elevational range: 130–240 m) reported fix success rates close to 100% in static tests [28, 29, 50]. Therefore, one explanation for why the two stations in this study performed poorly might be due topographic structure shading or limiting the GPS' access to satellites. However, generally the number of satellites used was high and it seems therefore unlikely that this caused the errors. Alternatively, data might have been lost due to lack of GSM coverage. This

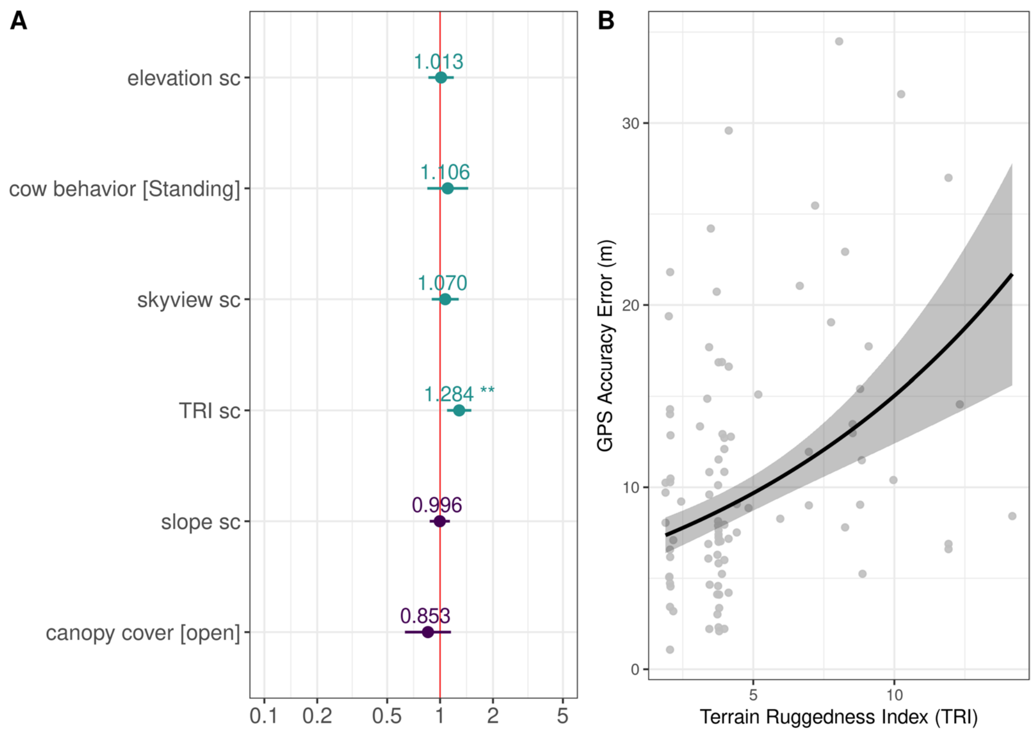

Fig. 7 **A** The GLMM model estimates for the mobile accuracy tests including their confidence intervals with 3.872 as reference level (intercept). The model included scaled numerical explanatory variables (sc) and were modeled on a gamma distribution with a log-link. The estimates are back transformed to the original scale in meters. Purple suggests a negative effect and green a positive effect. Furthermore, abrogated stars indicate the strength of evidence. And **B** the prediction plot for terrain ruggedness index (TRI) with the predicted GPS accuracy in meters. The black line represents the prediction with the gray ribbons as the standard error. The gray points are the original observations (n = 92)

could happen if the collar did not send any updates, as the collars are designed to send an update whenever a GSM connection is available, regardless of gaining a new GPS fix.

GPS performance
The GPS precision and accuracy errors we found are similar to those assessed in previous studies using static tests, with the average precision errors ranging between ± 1.5 and ± 4 m [26, 40, 50] and average accuracy errors between ± 4 and ± 10 m [22, 26, 28, 50]. Furthermore, we found, as expected, that GPS precision error of static collars was lower in open than closed canopy cover and decreased with increasing sky-view. Similarly, the GPS accuracy error was lower in open than closed canopy cover. However, here we found little evidence for an effect from the sky-view. Other studies report similar effects of canopy cover and reports stronger evidence for an effect of sky-view [21–24]. In addition, we also found that the number of satellites and the HDOP values are affected by the same variables. This shows that landscape and vegetation structures continue to affect GPS precision and accuracy errors.

Directional deviations
We found little evidence in the GPS accuracy model for stationary test that the south and west facing stations had slightly higher GPS accuracy error than the east and north facing stations. Additionally, none of the aspect categories followed the expected uniform distribution, indicating that there might be some directional deviation within the aspect categories. A few studies reported some effect of aspect on location errors and fix rates [22, 27], with only little evidence ($P < 0.25$). More recently, Zimbelman and Keefe [51] found some effect of topography, including aspect, on radio signals through GNSS satellites. Generally, there is not a clear pattern between studies, e.g., D'eon and Delparte [27] found lower GPS accuracy errors on southern slopes, while our results suggest higher errors. Additionally, our study also showed that the GPS positioned on the southern and western slopes the GPS used less satellites, which likely resulted in increased GPS errors. We speculate that the slight effects found across studies is more likely due to the local landscape structure, spacing and availability of satellites than generalizable patterns.

Mobile tests

We found that terrain ruggedness negatively affected the GPS accuracy error in the mobile tests, but there was no evidence for an effect of canopy cover nor sky-view. Contrary to expected, the cattle's behavior (standing or lying) did not affect the accuracy error. Forin-Wiart et al. [28] showed with static tests that when the antenna was placed downwards, i.e., under the body of an animal (simulated by bottles filled with a saline solution), the location error doubled. This effect seems similar to the difference of GPS accuracy error between the static and mobiles tests in this study. However, we did not find an additional shading effect of the collar when the cattle were lying down or canopy cover was dense. Our results confirm that static testing of GPS devices overestimates the performance [25, 26, 28, 29].

Limitations of our study

In the study design for the static test, the sample size was limited to one area with one 24-h period per station, which might lead to biases (e.g. lack of repetitions and heterogeneity in the data). Furthermore, it seems that the sky-view and aspect of the area were correlated. This is likely due to topographic differences, such as steeper slopes in the eastern and southern directions resulting in lower sky-view values. For future studies, we would recommend performing repeated measures at each of the stations and including multiple areas to avoid random variation related to weather, topography (to increase the range of variables), and satellite positions.

Measuring the true location of the cattle's positions generated an observer bias because the measurements were probably not as accurate as in the static tests. However, we assumed that this bias was consistent and therefore it is likely we still captured the general patterns of variables affecting the GPS accuracy error in the mobile test. Furthermore, the model for the mobile test had some heterogeneity of variance. Most likely this is due to habitat selection of cattle; they select for open, flat areas and often use roads for translocation [3, 52]. Therefore, the topographic variables of the mobile test might have a smaller range and be more homogeneous compared to those of the static tests. Increasing the sample size and using multiple herds in various topographies might improve the model.

Implementations of results

The collars used in this study had a virtual fence function, which is dependent on the GPS to work appropriately. Generally, our study confirms that, even though GPS technology is advancing, topographic variables still affect the GPS performance. Our results suggest an average GPS accuracy error of about 11 m when the collars are deployed on cattle. Furthermore, variation of the accuracy error might confuse the cattle as the border of the grazing area appears to be less fixed compared to conventional wired fences. The GPS accuracy error might be larger in rugged terrain. Therefore, it is important for farmers to consider GPS accuracy errors in designing their pasture enclosures, as the constitution of the landscape effects the magnitude of the error. To mitigate improper fencing function and risks for unclear and confusing signals and electric shocks, rugged areas for the virtual fence borders should be avoided.

In large grazing areas the GPS accuracy error results in a relatively small zone that cattle would avoid due to the sound warning given by the collar. However, virtual fences have been suggested as particularly advantageous compared to conventional wire fences in small and occasional grazing areas, where a physical fence entails a high cost or/and is undesirable most of the year [53]. In small pastures, the size would reduce the effective grazing area drastically and magnify the potential confounding influence of such errors when delineating boundaries. The design of a grazing area is most often not the sole choice of the farmer, but may be directed by the surrounding land and ownership structure also. For example, the median size of valuable semi-natural pastures in Sweden is two hectares [54]. Assuming an average GPS accuracy error of 11 m will result in the loss of about 30% of the pasture for effective grazing (Fig. 8). In general, semi-natural pastures are smallest in the forested districts, which makes the challenge of accuracy errors of virtual fences in closed habitats even more pronounced, especially as pastures are often of irregular shape, which increases the effect of the accuracy error. Therefore, considering the error in combination with the topography of the landscape is important for pasture design across a variety of applications of this emerging technology. For example, the results suggest a minimum pasture size of 5 to 10 ha, and ideally the virtual fence border should be placed in more open and less rugged terrain to reduce the error.

In larger areas and with well-trained cattle studies show the amount of electric shocks admitted to individuals is low with a decrease in electric shocks overtime [11, 20], but in smaller pastures animal welfare might be more compromised as the risk of warnings and electric shocks is higher. Despite size of pasture enclosure, provision of water, salt, and mineral supplements to grazing livestock fenced virtually should be done at a distance of at least 20–25 m from the fence, in order to be sure the animals are not obstructed from these resources by the virtually delineated fence.

Furthermore, large remote areas might not have consistent GSM coverage, especially if situated in valley bottoms or steep slopes. Therefore, when designing areas for

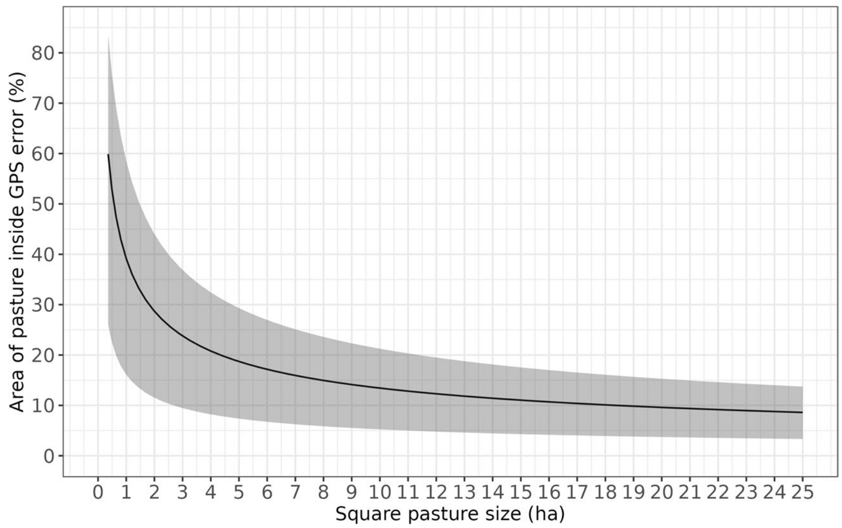

Fig. 8 Relation between square pasture sizes (ha) and the area of the pasture affected by the GPS accuracy error (%) using an error of 11 m (black line) and standard deviation of 6.8 m (gray ribbon)

free-ranging cattle we recommend to avoid creating borders through such areas. This might compromise animal welfare as the pasture border becomes more variable or does not work due to lack of GPS accuracy (< 3.5 m). Furthermore, the ability to monitor the cattle might be compromised as the collar might have lost GSM connection.

In research and management, understanding how cattle select and use the landscape is important for studying their effect on the environment, especially in free-ranging and multipurpose systems where objectives for forestry, nature conservation, and recreation are mixed. With the increasing availability of high-resolution satellite data understanding the performance of GPS devices becomes increasingly important. For example, in Norway a digital elevation model with a 1-m resolution is available (©Kartverket, hoydedata.no) and with the use of other bio-logging methods, such as high-resolution activity data (10 Hz), it becomes possible to look at cattle behavior and selection at an even higher resolution [55]. As studies utilize higher resolutions of data, it becomes increasingly important to consider and correct for GPS error, as the probability of misclassification of resource use or movement may increase.

Conclusions

This study showed GPS precision and accuracy are affected by landscape complexity, where the errors are larger in rugged terrain and closed habitats compared to flat and open land. Landscape complexity hence reduces the effectiveness of the fence, resulting in smaller usable grazing areas and increased risk for impaired animal welfare. Furthermore, a lack of GSM coverage leads to missing GPS fixes. Proper pasture management, where the farmer takes the potential lack of GSM coverage and landscape complexity into account in decisions of localization of the virtual fence borders, can mitigate those problems. In addition, our study suggests a minimum pasture size of 5 to 10 ha to avoid large reductions of the effective grazing areas, which also will contribute to less risk for deficient animal welfare. Overall, the use of commercially available virtual fence collars in remote boreal forests is a promising tool for both cattle management and research.

Abbreviations

GLMM	Generalized linear mixed model
GPS	Global positioning system
GSM	Global system for mobile communications
HDOP	Horizontal dilution of precision
LMM	Linear mixed model
TRI	Terrain ruggedness index

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40317-024-00389-8.

Additional file 1: **Figure S1.** Correlinearity plots for explanatory variables. **Figure S2.** Boxplot of the relation between sky-view and the cardinal directions (N, E; S, W).

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Author contributions
EV, MT and BZ conceived the study. BZ secured the funding. EV designed and conducted the study design and supervised the fieldwork. EV drafted the manuscript. BZ, MT, AH, RS, DS, and PW reviewed and commented on the initial drafts. All authors contributed to the ideas and edits to the manuscript and approved the submitted version.

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Availability of data and materials
The datasets generated and/or analyzed during the current study (including R-scripts) are available in the Dataverse NO repository, https://doi.org/https://doi.org/10.18710/TUCMOJ.

Declarations

Ethics approval and consent to participate
Ethical review and approval was not required for the animal study because this study used commercially available GPS/virtual fence collars in Norway and is approved by the Norwegian authorities for use on cattle. Written informed consent was obtained from the owners for the participation of their animals in this study.

Consent for publication
All authors agree to publish this work to *Animal Biotelemetry*.

Competing interests
The authors declare no competing interests.

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