Computers and Electronics in Agriculture 219 (2024) 108779

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

# On-animal sensors may predict paddock level pasture mass in rotationally grazed dairy systems

J.P. Edwards [a,*], M. Qasim [b], R.H. Bryant [c], C. Thomas [a], C. Wright-Watson [c], G. Zobel [d], M.B. Neal [b], C.R. Eastwood [a]

[a] DairyNZ Ltd, PO Box 85066, Lincoln 7647, New Zealand
[b] DairyNZ Ltd, Private Bag 3221, Hamilton 3240, New Zealand
[c] Faculty of Agriculture and Life Sciences, Lincoln University, PO Box 85084, Lincoln 7647, New Zealand
[d] AgResearch Ltd., 10 Bisley Rd., Hamilton 3214, New Zealand

ARTICLE INFO

*Keywords:*
Rotational grazing
Pasture mass
Animal behaviour
Animal sensors

ABSTRACT

Precision livestock farming aims to improve animal welfare and farm management using digital technology. We investigated the potential of individual on-animal sensors to predict paddock-level pasture mass, an important metric for grazing management in pasture-based dairy systems. The study consisted of four groups of 25 cows assigned to different pasture allocations (ranging from an estimated 80% to 120% of their energy requirements) over two 20-day experimental periods (late spring and late summer). Each cow was fitted with five sensors that measured a range of behaviours, including rumination time, eating/grazing time, activity and lying time. These data were used to build predictive models of pasture mass, which was estimated by calibrated rising plate meter. Our results show that rumination time was the most critical behaviour for predicting paddock-level pasture mass; the best predicted was post-grazing pasture mass (kg DM/ha) with a maximum Adjusted-$R^2$ value of 0.58 using a linear model. Including pasture and behaviour data at less than 24-hour resolution did not improve model performance, likely due to the importance of rumination, which is a diurnal behaviour. It is unclear whether this level of predictive ability is practically useful for making grazing management decisions; however, given its near real-time nature, low effort, and objectivity, the approach may provide value to farmers. Further evaluation is needed to determine how providing these data affects farmers' decision-making processes and therefore its value. In conclusion, our proof-of-concept experiment demonstrates the potential of individual on-animal sensors to predict post-grazing pasture mass, and this could help farmers make informed decisions for grazing management.

## 1. Introduction

Rotationally grazed pasture is an important feed source in many dairy systems globally (Neal and Roche, 2020). Pasture growth rate, and therefore feed availability, varies in response to many factors, such as temperature, soil moisture, nutrient status and grazing interval (Neal et al., 2019). Consequently, pasture growth rate and utilisation vary considerably, within a year and between farms. This variability results in pasture-based feed systems being complex, dynamic, and difficult to manage accurately (Beukes et al., 2019).

In response to this variation in pasture growth and quality, farmers use several strategic decisions to balance feed supply and herd demand. These decisions include block calving to align peak milk production with peak pasture growth rate (e.g., calving cows in mid to late winter, resulting in cows reaching peak milk production in mid-spring), choice of stocking rate (cows/ha), and use of supplementary feed (Macdonald et al., 2008; Macdonald et al., 2011). Despite these strategies, there are extended periods where pasture growth and herd demand are not matched, both within (e.g., seasonal growth surpasses cow intake) and between years (e.g., drought creates pasture deficit). Consequently, farmers also need to make tactical and operational decisions regarding land resource allocation for grazing across time and space. These decisions may include adjusting the area of pasture offered to the herd (e.g., building or using pasture on hand), setting aside area to conserve (e.g., to ensile), or to be converted into forage crop; the two latter points also require more decisions around timing of harvest or feeding (Glassey et al., 2010; Eastwood et al., 2017). These decisions require a trade-off between the often-conflicting requirements of pasture and animals (e.

* Corresponding author.
*E-mail address:* Paul.Edwards@dairynz.co.nz (J.P. Edwards).

https://doi.org/10.1016/j.compag.2024.108779
Received 2 September 2023; Received in revised form 21 December 2023; Accepted 20 February 2024
Available online 12 March 2024

g., promoting efficient pasture use while avoiding hunger, an important component of animal welfare). The effect of meeting cow requirements via consistency in pasture allocation results in improved milk production (Fulkerson et al., 2005).

Knowledge of paddock-level pasture mass is important for making these decisions. The regular ranking of paddocks by pasture mass, in conjunction with farm-level pasture growth rate, is a common approach for identifying likely pasture surpluses or deficits, managing pasture quality and selecting the order to graze paddocks (McCarthy et al., 2014; Eastwood and Dela Rue, 2017; Eastwood et al., 2017). A range of methods exist to estimate pasture mass, many of which are related to the height of the pasture, though all have limitations. Using a rising plate meter (RPM) to measure compressed sward height is one method (Lile et al., 2001), however, it requires significant time to walk a representative part of each paddock and is limited by the relationship between compressed height and dry matter mass (DM) changing between seasons (Thomson et al., 2001; Rennie et al., 2009; Murphy et al., 2021). Attempts to automate measurement of pasture mass have shown promise, but challenges around accuracy relative to existing approaches and/or frequency of data availability have resulted in limited adoption of these technologies (Eastwood et al., 2020). Consequently, operational grazing management decisions often rely heavily on farmers' experiential knowledge. While relying on past experience and personal judgement has historically been a feasible option for pasture management, a changing climate, larger farms, and changes in farm management staff create a need for data that is regular, robust, objective, and usable by the farm team. Thus, to avoid adding further cognitive burden to farmers facing increased complexity in farm decision making (Eastwood et al., 2022), there is a pressing need to develop alternative decision support options.

Pasture management can have a dramatic (positive or negative) impact on cow welfare in pasture-based dairy systems through the amount of feed offered. Monitoring cow behaviour, particularly as it changes over time, can provide indirect indicators of how the cow is experiencing her pasture environment. For instance, inadequate pasture allocation may result in a cow spending more time grazing to try to fulfil her motivation for satiety; this change will have carry-on effects on the cow's available time for lying and ruminating. Monitoring of these behaviour changes is possible with the increasing adoption of on-animal devices (sensors) in pasture-based systems (Dela Rue et al., 2020). Many of these sensors use accelerometers to capture movement and, using proprietary algorithms, classify this data into behaviours such as eating, ruminating, and activity (Neave et al., 2021). These classifications can assist in the early detection of oestrus, lameness, or calving (Clark et al., 2015; Mottram, 2016; O'Leary et al., 2020), and evaluating effects of management and weather on cow welfare (Neave et al., 2022a; Neave et al., 2022b). These sensors have also been used to estimate the pasture intake and liveweight gain on an individual cow basis (Greenwood et al., 2017; Rombach et al., 2018; Augustine et al., 2022). Individual animal behaviour classifications represent a potential dataset for estimating paddock-level pasture mass and trends, inexpensively and in near real-time. Combining these outcomes with behavioural time budgets could also provide management information to inform farmer decision making for maintaining cow welfare.

The objective of this experiment was to investigate whether pasture mass or allocation could be predicted using behaviour classifications from on-animal sensors. Our hypothesis was that the pre-grazing pasture allocation per cow could be predicted immediately after the cows left the paddock. Knowledge from this proof-of-concept study is useful for developers of on-animal sensors and could be used by farmers to increase the return on investment, reduce cognitive load for themselves and for staff (when making pasture management decisions), and provide objective data on herd feeding levels for quality assurance.

## 2. Materials and methods

### 2.1. Experimental site and setup

Four groups of spring calving Friesian-Jersey cross dairy cows (n = 25 cows/group) were established for two, 20-d experimental periods at the Ashley Dene Research and Development Station (Springston, Canterbury, NZ). Period 1 ran from 7-Nov-2021 to 26-Nov-2021 (late spring) and Period 2 ran from 27-Feb-2022 to 18-Mar-2022 (late summer). The use of animals was approved by the Lincoln University Animal Ethics Committee (AEC 2021–12).

Each group consisted of 5 primiparous and 20 multiparous animals. One month prior to Period 1 commencing, a group of 110 animals were milk sampled, weighed, body condition scored using a 10-point scale (Roche et al., 2009), and blocked on age (2, 3, 4–8 and 9+ years old), liveweight, days in milk, and milk production. They were then randomly allocated to four groups (10 animals left as spares). To allow for social habituation, the animals were drafted into their allocated group five days prior to each period commencing. On day 17 of Period 1, one animal was exchanged for an equivalent spare animal (i.e., same blocking group) due to a leg abscess. At the end of Period 1, the animals re-joined the main herd on the research farm. Five days prior to Period 2, animals were re-drafted into their same allocated groups. During Period 2, there were three animals that were swapped for equivalent spare animals on days 6, 14 and 20, two due to lameness and one due to generally appearing unwell and requiring treatment.

Each 20-d experimental period consisted of four 5-d blocks (Table 1). In Period 1 (late spring), during the first block, each group was allocated 0.35 ha/d with an estimated pasture mass of 2800 kg DM/ha. Assuming a target post-grazing residual mass of 1500 kg DM/ha or a compressed pasture height of ~35 mm (Ganche et al., 2013), this was equivalent to 18 kg DM/cow/d (100 % allocation; 39 kg DM/cow to ground level), the estimated requirements of the cows by back calculation of required energy for milk production (Nicol and Brookes, 2007). New pasture allocations were offered every 24 h following morning milking. During the second block, two groups received an over-allocation of pasture, 22 kg DM/cow/d (120 % allocation; 43 kg DM/cow to ground level). Allocation of pasture was managed by adjusting the pasture mass (by picking an appropriate area), or grazing area, or both, to separate the effects of management. For Group 1, over-allocation was achieved by increasing the area to 0.42 ha/d, while keeping the block 1 pre-grazing pasture mass (2800 kg DM/ha); for Group 2, the pre-grazing pasture mass was adjusted to 3050 kg DM/ha, while maintaining the block 1 area (0.35 ha/d). The other two groups received an under-allocation of pasture, 14 kg DM/cow/d (80 % allocation; 36 kg DM/cow to ground level). For Group 3, the under-allocation was achieved by decreasing the area to 0.28 ha/d, while keeping the block 1 pre-grazing pasture mass (2800 kg DM/ha); for Group 4, the pre-grazing pasture mass was adjusted to 2500 kg DM/ha, while maintaining the block 1 area (0.35 ha/d). All groups returned to a 100 % allocation for block 3. After this period, each group changed to the opposite allocation (i.e., Groups 1 and 2 received 80 %; Groups 3 and 4 received 120 %). The method by which the allocations were achieved remained consistent (i.e., Groups 1 and 3 had an adjusted area; Groups 2 and 4 had adjusted pre-grazing mass).

The same approach was used in Period 2 (late summer), however slight changes were made in response to the conditions (e.g., level of milk production). The 100 % allocation was targeted at 17 kg DM/cow/d and achieved with a pre-grazing pasture mass of 2700 kg DM/ha and 0.35 ha/d (assuming a 1,500 kg DM/ha residual pasture mass; 38 kg DM/cow to ground level). The 120 % allocation (41 kg DM/cow to ground level) was achieved with either 2,700 kg DM/ha and 0.43 ha/d (area adjusted) or 3,000 kg DM/ha and 0.34 ha/d (pre-grazing mass adjusted), and the 80 % allocation (36 kg DM/cow to ground level) was achieved with either 2,700 kg DM/ha and 0.28 ha/d (area adjusted) or 2,400 kg DM/ha and 0.38 ha/d (pre-grazing mass adjusted). Finally, the allocation method did not remain constant as it had in Period 1 (e.g.,

**Table 1**
Mean pre-grazing planned pasture allowance (to achieve the target allocation) and actual calibrated pasture allocations (kg DM/cow/day to ground level). Period 1 began on 7-Nov-2021 (cows' days in milk: 96 ± 15 days) and Period 2 began on 27-Feb-2022 (cows' days in milk: 209 ± 15 days). Each block was 5 days in length. The aim was to provide 100 % allocation (relative to requirements) for Blocks 1 and 3, and either over (120 %) or under (80 %) allocation for Blocks 2 and 4, depending on group. Allocations were achieved by adjusting area offered or pre-graze pasture mass with an assumed post-grazing residual of 1500 kg DM/ha.

| | | Period 1 (late spring) | | | Period 2 (late summer) | | |
|---|---|---|---|---|---|---|---|
| Group | Block | Allocation | Planned | Actual | Allocation | Planned | Actual |
| 1 | 1 | 100 % | 38.8 | 34.0 | 100 % | 38.3 | 40.4 |
| | 2 | 120 % by area | 42.5 | 46.3 | 120 % by area | 40.8 | 46.0 |
| | 3 | 100 % | 38.8 | 39.0 | 100 % | 38.3 | 34.2 |
| | 4 | 80 % by area | 35.6 | 32.5 | 80 % by mass | 36.3 | 28.5 |
| 2 | 1 | 100 % | 38.8 | 34.1 | 100 % | 38.3 | 40.2 |
| | 2 | 120 % by mass | 42.5 | 41.9 | 120 % by mass | 40.8 | 42.8 |
| | 3 | 100 % | 38.8 | 42.8 | 100 % | 38.3 | 34.6 |
| | 4 | 80 % by mass | 35.6 | 36.7 | 80 % by area | 36.3 | 26.2 |
| 3 | 1 | 100 % | 38.8 | 34.7 | 100 % | 38.3 | 39.9 |
| | 2 | 80 % by area | 35.6 | 29.4 | 80 % by area | 36.3 | 30.6 |
| | 3 | 100 % | 38.8 | 38.8 | 100 % | 38.3 | 34.6 |
| | 4 | 120 % by area | 42.5 | 46.8 | 120 % by mass | 40.8 | 34.4 |
| 4 | 1 | 100 % | 38.8 | 33.6 | 100 % | 38.3 | 39.8 |
| | 2 | 80 % by mass | 35.6 | 32.4 | 80 % by mass | 36.3 | 34.0 |
| | 3 | 100 % | 38.8 | 37.8 | 100 % | 38.3 | 34.7 |
| | 4 | 120 % by mass | 42.5 | 45.7 | 120 % by area | 40.8 | 40.8 |

Group 1 which received the 120 % allocation by adjusting the area went to the 80 % allocation by adjusting the pasture mass for block 4).

As the aim of the experiment was to use behaviour classifications from sensors to predict the level of allocation, the experimental design was chosen so that each group experienced a range of pasture allocations; no behavioural comparisons between the three levels of allocation were hypothesized nor planned. The block duration of 5 days was chosen to allow the animals time to adjust to their allocation. In total, 160 data points were generated for use in the pasture allocation prediction (4 groups × 20 days × 2 experimental periods).

### *2.2. Pasture and allocation measurement*

The pasture allocations described in the preceding section were estimated using a rising plate meter (RPM; Period 1, Platemeters G1000, GPSit, Tauranga, New Zealand; Period 2, Jenquip EC20, Feilding, New Zealand) that measured compressed pasture height in mm. The target area allocation was attained by temporary electric fencing within 4.5 ha paddocks and was measured using a 1 m wheel. A minimum of 100 compressed height measurements were taken in a W pattern with the RPM per allocation area to account for spatial variability of pasture mass and a mean calculated. This was converted to pasture mass (kg DM/ha) using the manufacturers standard equation of 28× mm compressed height +500 for pastures with a high proportion of green material. The pre-grazing pasture mass was estimated the day before grazing and small adjustments (±0.02 ha) to the area offered were permitted if the pasture mass was above or below the target to achieve the 80 %, 100 % or 120 % allocation. After the temporary fencing was set up, the GPS coordinates of each corner were recorded using a Reach M2 (Emlid, Hungary) to determine the actual area offered.

In addition to the pre-grazing pasture assessment, the compressed height was measured 5 times at approximately equal intervals during daylight hours to enable a pasture disappearance curve to be determined; this corresponded to approximately 10:30, 13:00, 15:30, 18:30 and 20:30. Finally, post-grazing pasture residual was measured the next morning after the group had exited the allocated area, using the same RPM methodology described earlier.

During each 5-day block, as well as 5 and 10 days prior (Block −1 and −2) and 5 days following each experimental period (Block 5), a total of 36 quadrats (0.2 $m^2$) were cut to ground level for post-experiment calibration of the RPM. Four quadrats were cut in three representative areas of each stage of pasture growth (pre-grazing, at intermediate pasture mass, post-grazing) to make the total of 36 (4 quadrats × 3 areas × 3 growth stages). Cut pasture was washed and dried at 60 °C for 48 h and then weighed and converted to kg DM/ha pasture mass. Linear regression was used to determine the relationship (calibration equation) between compressed pasture height from the RPM and the pasture mass for each 5-day period (Fig. 1). A second linear regression was performed for both the slope and intercept coefficients (by time) and tested for significance ($P < 0.05$). The slope was not significant for the intercept coefficients, so these were averaged to produce a single intercept value for each experimental period. The slope coefficients were significant. The predicted slope coefficient for each day and the intercept for each experimental period was combined with the RPM measurements of each allocation area to derive calibrated pasture mass for each RPM measurement. The final equations used to convert compressed pasture height (CPH; mm) to kg DM/ha were: $(25.2 + 0.34 \times \text{day of period}) \times \text{CPH} + 469$ (Period 1) and $(34.4 - 0.53 \times \text{day of period}) \times \text{CPH} + 286$ (Period 2). During the experiment, the values derived from the standard plate meter equation were used for pasture allocation; however, for the analysis, the more accurate, calibrated pasture mass was used.

Pasture samples for nutrient composition (crude protein, ADF, NDF, digestibility of organic matter in DM; DOMD) were collected by snipping a handful of pasture at estimated grazing height every 4$^{th}$ step along a random transect across at least 20 m of each area allocated, (i.e., 160 samples). A 30 g (fresh weight) sub-sample was set aside and combined to create a bulked sample for each group × block (i.e., 2 experimental periods × 4 blocks × 4 groups = 32 bulked samples). These were separated into ryegrass leaf and sheath, ryegrass reproductive stem, white clover, herbs, and other grass species, weed species and dead matter components, dried at 60 °C for 48 h, and the dry weight of each component recorded. A second sub-sample of approximately 100 g (fresh weight) was dried at 60 °C for 48 h and ground to 1 mm and analysed using near-infrared spectrophotometer (NIRS; FOSS NIRSystems 5000, Foss Electric, Hillerød, Denmark). Metabolizable energy concentration (ME; MJ/kg DM) was estimated using the equation $\text{ME} = \text{DOMD} \times 0.16$ (AFRC, 1993).

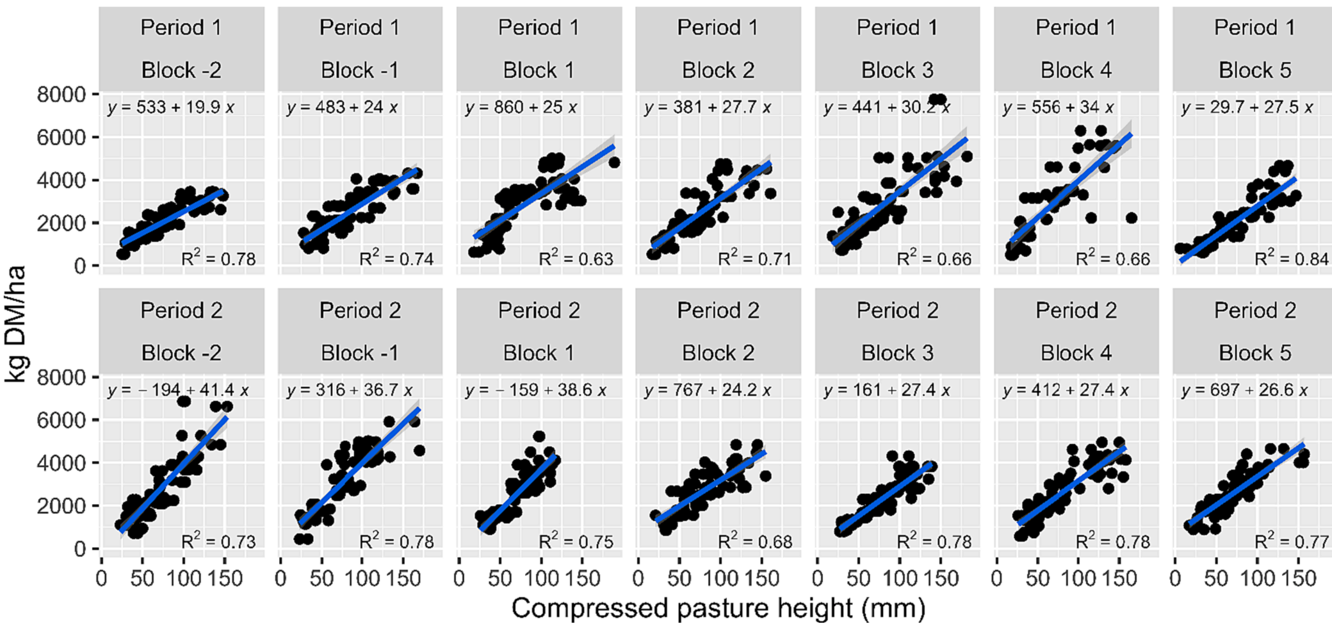


**Fig. 1.** Linear calibration equations for the rising plate meter (RPM) generated from 36 quadrats (0.2 $m^2$) taken every 5 days, including 2 occasions prior to and 1 occasion after the main experimental blocks (1–4).

### 2.3. Animal measurements

Each animal had a total of 5 behaviour monitoring sensors (Fig. 2). An IceQube pedometer (Peacock Technology Ltd, Stirling, Scotland) was attached to the cows' right hind leg. A CowManager tag (CowManager B. V., Harmelen, Netherlands) was attached to a button ear tag (on the side free from any management tags) while cows were restrained in a crush. While the animals were still restrained, a smaXtec SX2 rumen bolus (smaXtec animal care GmbH, Graz, Austria) was inserted orally. To minimize holding time, cows were restrained a second time the next day to apply the Agersens eShepherd neckband (Gallagher Group Ltd, Hamilton, New Zealand) and AfiCollar sensor (Afimilk Ltd, Kibbutz Afikim, Israel). The eShepherd neckband was used as a passive monitor only, no virtual fencing functionality was used in the experiment. The AfiCollar sensor was attached to the eShepherd neckband to minimize the weight of sensors worn around the neck of the animal. Details of the data provided by each sensor can be found in Table 2. Animals were fitted with their sensors at least 5 days prior to each experimental period; the AfiCollar and eShepherd neckbands were removed from the cows after completion of Period 1 and were reapplied for Period 2. Apart from several IceQubes that were removed due to having shifted or caused rubbing, these sensors were left on the leg until after Period 2. Data was processed by the manufacturers' proprietary algorithms downloaded using the manufacturers' provided software. Between Period 1 and 2, there was a software update to AfiCollar. Consequently, Afimilk Ltd retrospectively ran both versions of the software over the raw accelerometer data to produce a version 1 and version 2 of each cows' behaviour estimates.

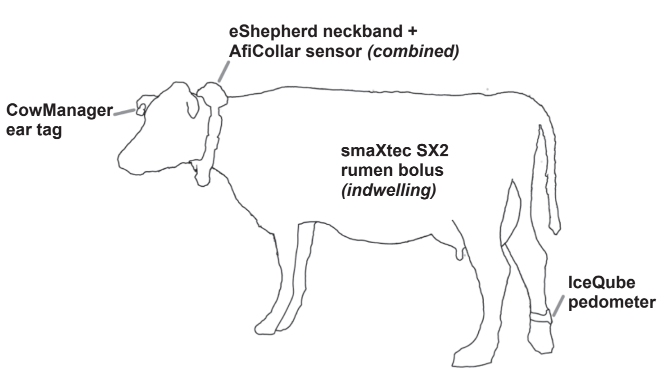


**Fig. 2.** Location on the cow of the 5 sensors used in the experiment.

Animals were milked twice per day at approximately 06:30 and 15:00 through a 54-stall rotary dairy parlour (Waikato Milking Systems, Hamilton, New Zealand), with automatic cup removers. For contextual information, milk weight was recorded by in-line milk meters (AfiMilk Ltd) at each milking.

### 2.4. Data analysis

Mean calibrated pasture mass for pre- and post-grazing (kg DM/ha) were combined with the grazing area allocated to determine the amount of feed and divided by the number of cows to determine the value in kg DM/cow (to ground level). Pasture disappearance ('disappearance') was calculated by subtracting post-grazing ('post') mass from the pre-grazing ('pre') mass. Overall, there were a total of six combinations of metrics, two pasture metrics (mean calibrated kg DM/ha, mean calibrated kg DM/cow) and three types (pre, post and disappearance).

Both animal behaviour and pasture mass data were transformed into daily time-series for the four groups over a period of forty days (20 days from each experiment). The final dataset consisted of 40 observations for each group, totalling 160 observations. For animal behaviour data, we calculated the daily total for each behaviour and cow individually, and then estimated daily average group values. Prior to averaging, we examined the data at individual cow level reported by each sensor, considering the recording frequency specific to each sensor type (e.g., hourly for AfiCollar). Instances of missing data resulting from sensor failures or malfunctioning sensors were identified and addressed. Notably, we omitted data from cows affected by sensor malfunctions; for instance, four cows from disparate groups exhibited inconsistent data patterns as reported by the IceQube sensor, and consequently, these data points were excluded from the dataset. We postulate that the omission of a small number of cows (one or two) from a given group due to sensor malfunctions would exert negligible influence on the calculated group average. This inference is predicated on the assumption that the group average, computed using the untainted data from the majority of cows, remains robust and representative despite the selective exclusion of a

**Table 2**
Details of behaviour classifications provided by each of the five sensors (n = 160; 4 groups × 20 days × 2 experimental periods; data averaged from 25 cows/group) and accompanying milk production and pasture allocation.

| | | Period 1 (late spring) | | | | Period 2 (late summer) | | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable[1] | Sensor[2] | Min | Mean | Max | SD | Min | Mean | Max | SD |
| *Activity behaviour* | | | | | | | | | |
| Active (min/d) | CowManager | 105 | 165 | 355 | 44.6 | 81 | 136 | 235 | 37.4 |
| High Active (min/d) | CowManager | 92 | 133 | 214 | 25.4 | 123 | 186 | 256 | 28.9 |
| Not Active (min/d) | CowManager | 176 | 264 | 358 | 36.8 | 195 | 283 | 432 | 44.7 |
| Moving (min/d) | eShepherd | 122 | 175 | 236 | 27.5 | 113 | 177 | 229 | 27.8 |
| Activity Index | smaXtec | 188 | 247 | 297 | 23.6 | 229 | 279 | 343 | 23.5 |
| Steps (n/d) | IceQube | 3,474 | 5,635 | 7,433 | 821.4 | 4,644 | 5,970 | 7,689 | 625.3 |
| Feeding | | | | | | | | | |
| Eating (min/d) | CowManager | 344 | 427 | 501 | 34.2 | 394 | 454 | 514 | 26.8 |
| Eating (min/d) | AfiCollarV1[3] | 86 | 224 | 415 | 70.2 | 121 | 360 | 502 | 83.0 |
| Eating (min/d) | AfiCollarV2[3] | 191 | 377 | 559 | 75.1 | 197 | 474 | 616 | 86.6 |
| Grazing (min/d) | eShepherd | 428 | 511 | 618 | 33.7 | 438 | 515 | 594 | 36.8 |
| Positions | | | | | | | | | |
| Resting (min/d) | eShepherd | 543 | 612 | 678 | 29.4 | 484 | 570 | 651 | 34.2 |
| Lying (min/d) | IceQube | 443 | 538 | 640 | 42.7 | 398 | 533 | 661 | 45.1 |
| Standing (min/d) | IceQube | 800 | 902 | 997 | 42.5 | 779 | 906 | 1,042 | 45.5 |
| Transitions (no.) | IceQube | 12 | 17 | 21 | 2.1 | 10 | 15 | 23 | 2.3 |
| Transitions Down (no.) | IceQube | 6 | 8 | 10 | 1.1 | 5 | 8 | 11 | 1.2 |
| Transitions Up (no.) | IceQube | 6 | 8 | 10 | 1.1 | 5 | 8 | 11 | 1.3 |
| Rumination | | | | | | | | | |
| Ruminating (min/d) | CowManager | 272 | 456 | 567 | 52.3 | 254 | 381 | 455 | 46.2 |
| Ruminating (min/d) | smaXtec | 361 | 492 | 568 | 41.1 | 359 | 432 | 504 | 33.1 |
| Rumination (min/d) | AfiCollarV1[3] | 309 | 439 | 553 | 59.9 | 231 | 317 | 438 | 40.9 |
| Rumination (min/d) | AfiCollarV2[3] | 204 | 402 | 533 | 65.3 | 195 | 302 | 413 | 46.4 |
| Other | | | | | | | | | |
| Milk weight (kg/cow/d) | AfiMilk | 18 | 21 | 23 | 1.3 | 13 | 17 | 19 | 1.1 |
| Pre-grazing allocation[4] | RPM and CC[5] | 27 | 38 | 51 | 6.0 | 24 | 36 | 52 | 5.6 |
| Post-grazing residual (kg DM/ha) | RPM and CC[5] | 1387 | 1761 | 2500 | 210 | 1114 | 1535 | 1977 | 186 |
| Dry matter % | Oven | 18 | 22 | 29 | 2 | 13 | 19 | 25 | 3 |
| Acid detergent fibre % | NIRS | 18.7 | 22.1 | 25.8 | 1.5 | 19.4 | 21.7 | 24.3 | 1.1 |
| Neutral detergent fibre % | NIRS | 31.9 | 38.3 | 43.7 | 3.0 | 26.2 | 35.0 | 43.6 | 3.0 |
| Crude protein % | NIRS | 11.8 | 16.2 | 21.2 | 2.1 | 13.8 | 17.7 | 22.7 | 1.9 |
| Metabolisable energy (MJ/kg DM) | NIRS | 11.4 | 12.4 | 13.0 | 0.4 | 11.6 | 12.3 | 12.9 | 0.3 |
| Ryegrass leaf | Botanical | 61 | 79 | 88 | 9 | 51 | 67 | 77 | 8 |
| Ryegrass seedhead | Botanical | 0 | 8 | 27 | 9 | 1 | 4 | 17 | 4 |
| Clover | Botanical | 1 | 5 | 9 | 2 | 1 | 10 | 22 | 7 |
| Other | Botanical | 3 | 8 | 16 | 4 | 0 | 19 | 35 | 10 |

[1] Each manufacturer's behavioural definitions and algorithms are proprietary; thus, the behaviours are named according to the manufacturer's classification (e.g., 'eating' for Cow Manager and 'grazing' for eShepherd are not equivalent).
[2] Recording Frequencies: CowManager ear tag = 60 min; eShepherd collar = 10 min; smaXtec rumen bolus = 60 min; Leg-based IceQube = 15 min; AfiCollar (clipped to eShepherd neckband) = 60 min; AfiMilk milk meters = twice daily; RPM, CC, Oven and NIRS = daily; Botanical = every 5 days.
[3] A software update occurred between Period 1 and Period 2, values reported by each version for both periods are reported.
[4] Expressed in terms of mean kg DM/cow to ground level.
[5] RPM = rising plate meter; CC = calibration cuts.

limited subset of cows affected by sensor anomalies.

All behaviour values are reported descriptively (Table 2); however, behaviours were excluded from the modelling if supported by science-based evidence (e.g., Pereira et al. (2018) reported poor accuracy for 'activity' when compared to live observations for CowManager sensors, so activity was not included).

To determine the hours the group was on pasture (accounting for time spent milking and walking to/from the parlour), the eShepherd GPS locations were intersected with the polygon created by four corners of the area allocated to determine if the point was inside the area or not. If less than 60 points out of a possible 150 (6 points/h × 25 animals) were in the allocated area, then the group was classified as having left for milking during that hour period. Entry times following each milking were determined as the minimum timestamp and the exit times were the maximum timestamp within the hour period(s) the group was at milking. The time in the allocated area was the sum of the time between the group entering following morning milking to the time they left for afternoon milking plus the time between re-entering the allocated area after the afternoon milking and the time they left the next morning for milking.

Fig. 3 represents a correlation plot between key variables in our dataset. The correlation plot was drawn using *chart.Correlation* function from the PerformanceAnalytics library in R (R Foundation for Statistical Computing, Vienna, Austria) with default *pearson* correlation coefficient. We used the most recent versions of R (4.3.0) and its libraries at the time of the submission of this paper.

We applied regression models, using the default statistics package in R, to analyse the empirical relationship between pasture mass and animal behaviour. Equation (1) represents the generic equation of this relationship:

$$y_i = \beta_0 + \beta_1 X_n + e \quad (1)$$

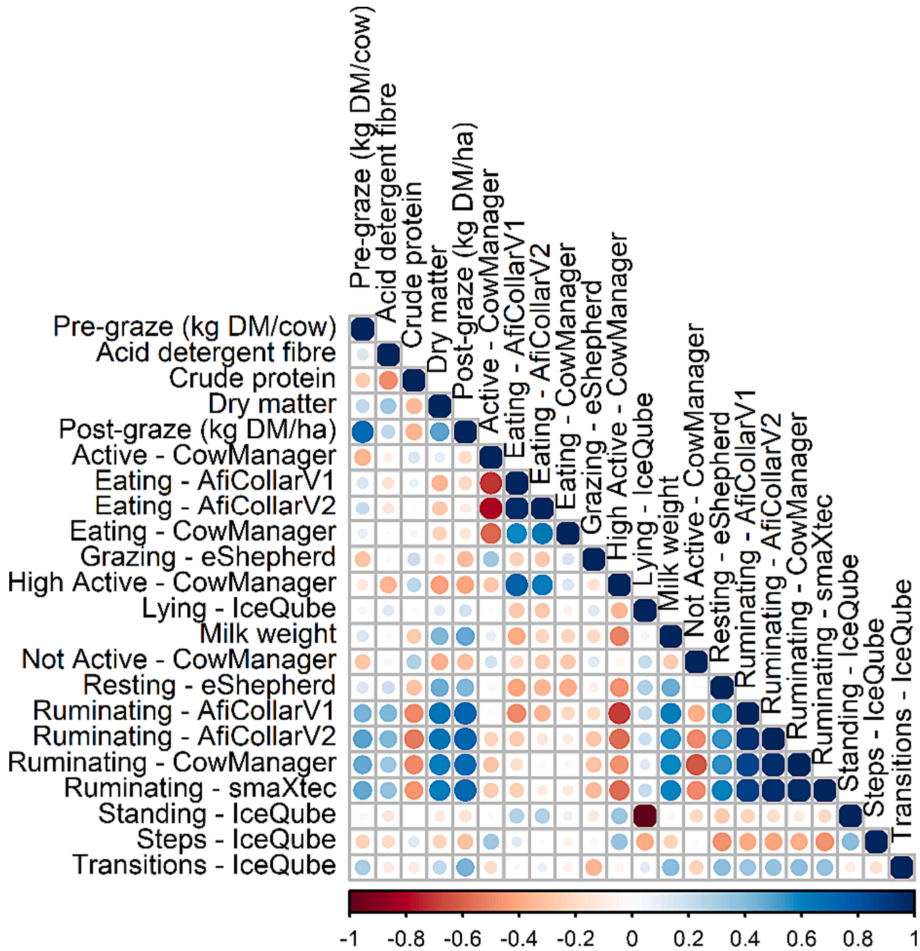


**Fig. 3.** Correlation between averaged pasture allocation and averaged sensor-recorded behaviours (n = 160; 4 groups × 20 days × 2 experimental periods). Size and colour of bubble represents the strength of the correlation (value presented on x-axis). Each manufacturer's behavioural definitions and algorithms are proprietary; thus, the behaviours are named according to the manufacturer's classification (e.g., 'eating' for CowManager and 'grazing' for eShepherd are not equivalent). 'Transitions' for IceQube refer to the transition between lying and standing behaviour.

Where:

$y$ pasture metric: pre, post, disappearance.

$i$ Measurement units of pasture cover: Kg DM/cow, kg DM/ha.

$X_n$ matrix of animal behaviour recorded by a given sensor, 24 h sum of each cow's behaviour, averaged across the group. Unless otherwise stated, each model used data from a single sensor. See Table 2 for the variables provided by each sensor.

$\beta_0, \beta_1$ linear regression coefficients and $e$ is the error term.

For a comprehensive analysis, we ran our regression models with slight variations in pasture measurement, such as the transformation of pre- and post- measures on a scaled rank from 1 to 10 to eliminate possible measurement bias, and three-day rolling averages. In addition, we conducted model performance comparisons using animal activity at sub-group levels for cows and heifers, and models with the additional explanatory variable number of grazing hours (spent inside the allocated area on a given day). Furthermore, we ran our models with several practical combinations of sensor data and aggregation methods, including using a modelled disappearance curve using the high-resolution time-series data consisting of 6 windows of time within each day between morning and evening (this particular analysis was conducted using AfiCollarV2 data only).

To calculate intraday pasture disappearance curves, we employed asymptotic regression, a non-linear model well-suited for capturing the dynamics of diminishing returns. This approach allowed us to model the relationship between time and pasture disappearance during the day, accounting for the natural decline in pasture availability as grazing occurs. By fitting an asymptotic regression model to the observed data, we were able to estimate the initial pasture availability and the rate at which it disappeared throughout the day.

Finally, we applied semi-supervised machine learning methods to benchmark the predictive power of our standard linear models. We implemented a k-fold cross-validation algorithm (Refaeilzadeh et al., 2009) on lasso regression models leveraging the "caret" package (Kuhn, 2008) in R, using data from AfiCollarV2, CowManager, and smaXtec, with the value of k set to 10.

## 3. Results

Table 1 summarises the planned and actual average pasture allocations for the four groups across the four blocks and two experimental periods. All behaviours, as captured by the five animal-based sensors, as well as pasture quality and composition, are summarised descriptively in Table 2. Sensors reported proprietary behaviours (e.g., indices, behavioural transitions etc.), as well as several overlapping behaviours (e.g., feeding, ruminating, resting/lying). Fig. 3 illustrates the correlations among these various behaviours. Strong positive correlations (r = 0.95 to 0.96) were present between rumination time recorded by the AfiCollarV2, CowManager, and smaXtec. A positive correlation was also observed for eating time recorded by the AfiCollarV2 and CowManager (r = 0.64). Despite the positive relationships, large differences existed for group daily rumination (difference in mean value: Period 1 – 90 min/d; Period 2 – 130 min/d) and feeding (e.g., difference in mean value:

Period 1 – 134 min/d; Period 2 – 61 min/d) between the lowest and highest sensor-recorded mean values (excluding AfiCollarV1; Table 2). The variability of rumination time within animal-days is illustrated in Fig. 4. In terms of the relationship between pasture availability and animal activity, rumination time was strongly correlated with pre- (r = 0.47 to 0.49) and post-grazing (r = 0.69 to 0.73) pasture mass (Fig. 3). Rumination time was also correlated with dry matter percent (0.62 to 0.65), crude protein (−0.46 to −0.53) and acid detergent fibre (0.33 to 0.41) of the pasture.

Comparing AfiCollarV1 and AfiCollarV2, AfiCollarV2 had Adjusted-$R^2$ values ranging from the same to 0.06 less than AfiCollarV1, however, AfiCollarV2, being the current version, was used for further analysis. Of the pasture measures, post-grazing pasture mass (kg DM/ha) was best predicted by several sensors which recorded rumination and feeding behaviour (AfiCollarV2, smaXtec, CowManager; Adjusted-$R^2$ = 0.48 to 0.52; Fig. 5), while pre-grazing pasture allocation (Adjusted-$R^2$ = 0.22 to 0.30) and disappearance (Adjusted-$R^2$ = 0.01 to 0.16) were not well predicted. Sensors which recorded eating and activity only (eShepherd) or activity only (IceQube) did not predict pasture mass well (Adjusted-$R^2$ < 0.27; Fig. 5). Inclusion of the number of hours that groups spent inside the allocated area as an additional variable did not substantively improve the best-performing models, except for IceQube (where Adjusted-$R^2$ increased by a maximum of 0.04). This observation is consistent with the fact that rumination continues even when the cows are outside the paddock (e.g., at milking). When compared to ranking (instead of using actual values), using a 3-d rolling average yielded slight improvements in the predictive ability in some models, by a maximum of 0.04 (Fig. 5). Parity (cow, heifer), did not improve the fit of the models (relative to the models in Fig. 5, $R^2$ ranged from +0.01 to −0.08). The performance models with intraday pasture disappearance curves and corresponding AfiCollarV2 animal behaviour data were not better than the daily models (Adjusted-$R^2$ = 0.26 for kg DM/ha and 0.21 for kg DM/cow). Combining data from some sensors only slightly improved predictive performance. For instance, when combining data from AfiCollarV2 and IceQube for predicting the 3-day rolling average of post-grazing mass (kg DM/ha), the Adjusted-$R^2$ increased from 0.56 to 0.59 (significant variables being rumination time and number of

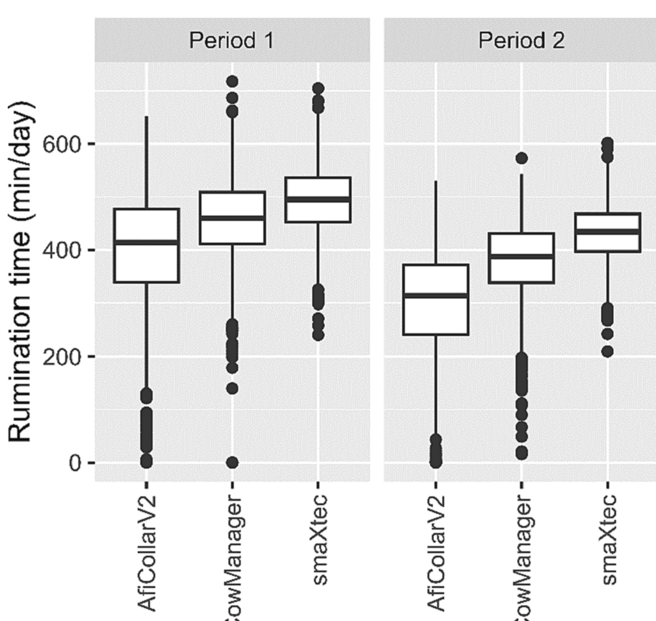


**Fig. 4.** Boxplot illustrating the variation in daily rumination time between animals and days for each period of the experiment. Number of data points were 1920, 1940, 1960 in Period 1, and 1880, 1940 and 1920 in Period 2 for AfiCollarV2, CowManager and smaXtec, respectively. The theoretical maximum was 2000 points (100 cows × 20 days).

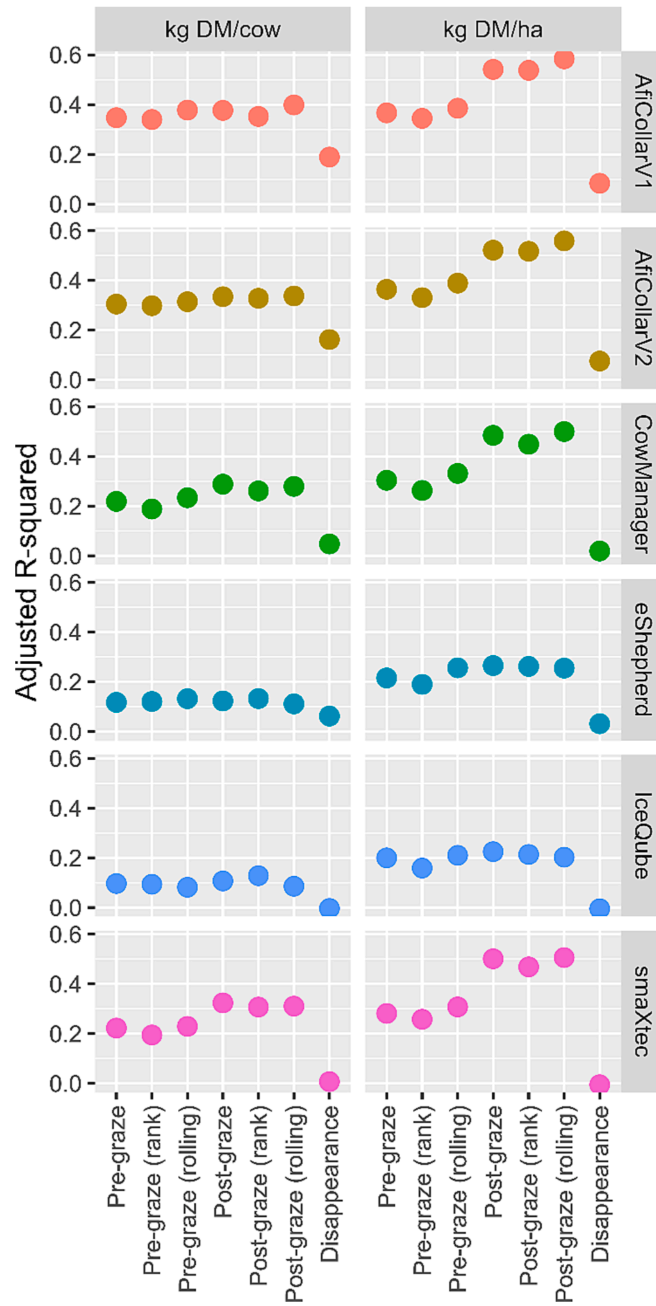


**Fig. 5.** Adjusted-$R^2$ values for various linear models relating sensor-recorded behaviours (n = 160; 4 groups × 20 days × 2 experimental periods) to pasture parameters measured as kg DM/cow or kg DM/ha.

transitions). Including pasture quality data (acid detergent fibre, crude protein and dry matter percent) generally improved the Adjusted-$R^2$ values over those presented in Fig. 5, for AfiCollarV2, CowManager and smaXtec by −0.01 to 0.07, for eShepherd by 0 to 0.13, and IceQube by 0.02 to 0.20. The maximum increases for eShepherd and IceQube were for 3-d rolling average post-grazing residual (kg DM/ha), which increased to 0.38 and 0.40, respectively, from the values presented in Fig. 5. The maximum increases to Adjusted-$R^2$ for AfiCollarV2, CowManager and smaXtec were for 3-d rolling average pre-grazing pasture mass (kg DM/ha).

Table 3 presents a summary of the best-performing models from Fig. 5. Post-grazing pasture cover (3-day rolling average) was predicted by rumination (smaXtec and AfiCollarV2) and rumination and eating (CowManager). The direction and magnitude of the coefficients for

**Table 3**
Coefficients of the best performing models presented in Fig. 5, between sensor-based behaviours and 3 day rolling mean of post grazing residual (kg DM/ha; n = 160; 4 groups × 20 days × 2 experimental periods). Significance depicted by asterisks (** = p < 0.01; *** p < 0.001), standard errors in brackets.

| | AfiCollarV2[1] | CowManager | smaXtec |
|---|---|---|---|
| Constant (kg DM/ha) | 1017.65*** (70.24) | 1043.59*** (161.75) | 154.38 (256.09) |
| Rumination time (mins/day) | 1.88*** (0.13) | 2.15*** (0.17) | 3.01*** (0.31) |
| Eating time (mins/day) | −0.06 (0.11) | −0.64** (0.32) | |
| Activity index (unitless) | | | 0.42 (0.52) |
| $R^2$ | 0.565 | 0.506 | 0.512 |
| Adjusted $R^2$ | 0.559 | 0.500 | 0.506 |
| RMSE (kg DM/ha) | 126 | 134 | 133 |

[1] A software update occurred during the study period and was retrospectively applied to the entire dataset by the manufacturer. Modelling was performed using the most recent version (V2) only.

rumination were similar across the three sensors. The k-fold cross-validation algorithm on lasso regression models yielded $R^2$ values of 0.58, 0.52 and 0.53 for AfiCollarV2, CowManager and smaXtec, respectively, compared to the standard linear model values of 0.57, 0.51 and 0.51 in Table 3. Fig. 6 presents the actual versus predicted values from the standard linear and semi-supervised machine learning models. The models appeared to underestimate post-grazing mass at the upper end of the range.

## 4. Discussion

The objective of this study was to investigate whether a relationship could be established between behaviour classifications from on-animal sensors and pasture parameters to provide objective data on herd-level feed allocation. The results suggest that this is feasible, but the accuracy may limit its usefulness. We hypothesised that calibrated pre-grazing pasture allocation (kg DM/cow) would be the pasture parameter that had the strongest relationship with animal behaviours. We expected per cow, rather than per ha, values to perform better because they account for the area offered as well as the number of animals in the area. Furthermore, kg DM/cow feed allocation is an important driver of milk production. However, pre-grazing allocation (kg DM/cow) accounts for the feed available to ground level. A variety of factors may impact how much of this is left behind, and these will not necessarily be encompassed in the behaviour captured by the sensors. Indeed, the best predicted pasture parameter was post-grazing pasture residual (kg DM/ha). Post-grazing residual is also an important parameter for pasture management, alongside the proportion of the farm grazed each day, as it influences regrowth and pasture quality at subsequent grazings. It is arguably the best metric for illustrating the trade-offs between maximising pasture performance and animal performance, when excluding potential animal welfare implications, such as hunger (Gregorini et al., 2009). Objective knowledge of post-grazing residual is useful for improving farm system profitability (optimising pasture and animal performance) and may also reduce the cognitive load of farmers and their staff. For example, the availability of sensor data may result in a farmer feeling motivated to make decisions. McCown et al. (2012) suggests that such data may override the typical judgement the farmer might use in exchange for a perceived increased accuracy. We suggest this shift could help prevent the cognitive stress associated with increasingly more complex daily decisions farmers are tasked with; however, data must be presented in a condensed and usable format (Fountas et al., 2006) and in a way that is dynamic and easily updatable (Öhlmér et al., 1998). In addition, from an animal welfare perspective, post-grazing residual gives an indication of feed allocation, with consistent residuals being an indication of consistent feeding levels. Inconsistent pasture allocation can have adverse behavioural effects. For

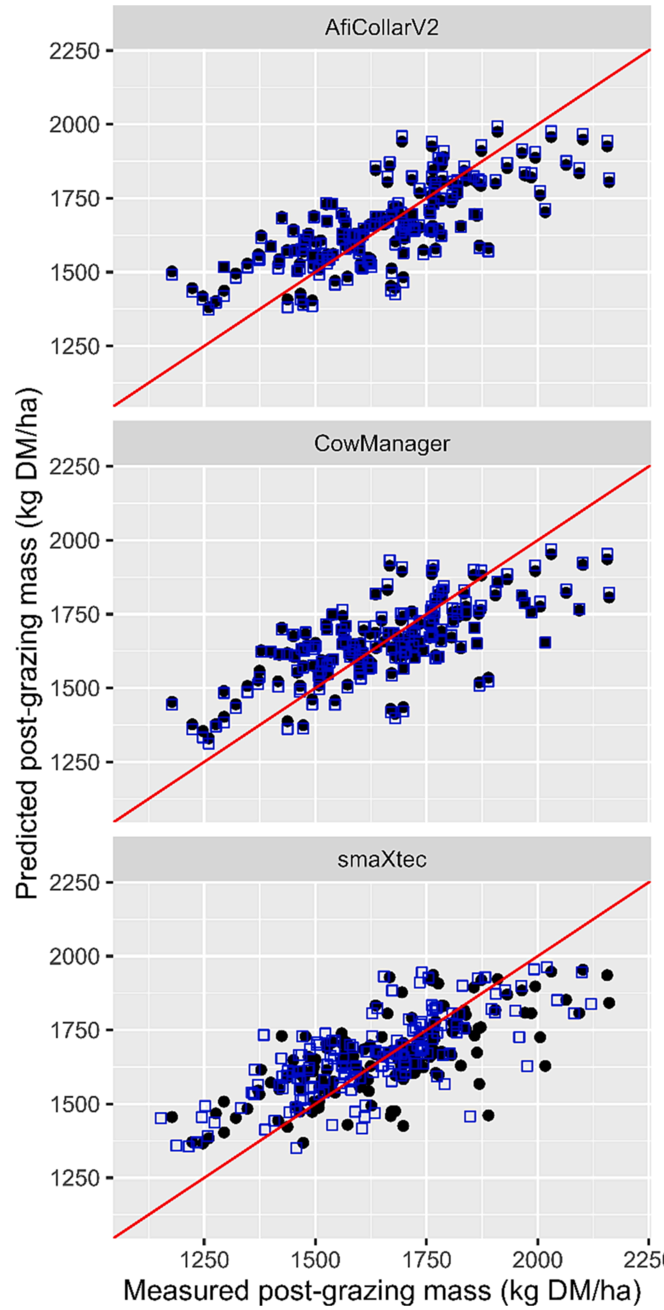


**Fig. 6.** Actual vs predicted post-grazing pasture cover (3-day rolling average) during the two 20-day experimental periods (n = 40) using the 3 best predicting sensors, using the equations from Table 3 (dots) and predictions from a semi-supervised machine learning k-fold cross-validation algorithm on a lasso regression model (squares).

instance, when receiving a new pasture allocation, cows will increase their intake rate to ingest large amounts of grass to address energy requirements and hunger (Kennedy et al., 2009; Chilibroste et al., 2015); this coupled with reduced mastication, may result in altered rumination behaviour and longer rumen retention times, which then in turn impact future feed intake, ultimately compromising energy availability, as reviewed by Gregorini et al. (2017). Thus, including estimates of post-grazing residuals into time budget analyses evaluating the welfare of cows, e.g., Neave et al. (2021), may strengthen the outcomes of such studies.

A possible explanation for why post-grazing residual (kg DM/ha) was the best predicted metric relates to the way pasture is offered under rotationally grazed pastoral dairy systems. In such grazing dairy systems, optimum profitability is achieved through careful balancing of animal and pasture production. For example, with a comparative stocking rate of ∼80 kg liveweight/t DM of feed available (Macdonald et al., 2008; Macdonald et al., 2011), when grazing pressure is reduced, pasture utilisation declines, while higher grazing pressure compromises animal performance. When allocating pasture (kg DM/cow) at a daily level, it is generally assumed that milking cows will not graze below 1500 kg DM/ha; in this experiment, the 80 % and 120 % allocations were determined using this assumption. While cows likely ate more when allocated 120 % (compared to what they would consume at 100 % allocation), generally they did not consume the full additional 20 % leaving behind higher post-grazing residuals, as reported previously (Pérez-Prieto and Delagarde, 2013). Conversely, cows in the 80 % allocation could partially make up for the 20 % deficit by grazing below 1,500 kg DM/ha (Table 2). The cows in the 120 % allocation would be expected to graze less and ruminate more, while those in the 80 % allocation would likely have an inverse pattern of behaviour (Gregorini et al., 2012); this aligns with the models' reasonable ability to predict post-grazing residual (kg DM/ha) using these behaviours. Furthermore, in over half of the possible pasture allocations (8 block/group combinations in Period 1, and 9 in Period 2) cows received on average, less pasture allocation than planned. This was due to paddock (pasture mass) availability and use of the RPM with a standardised equation, which would have introduced error (Table 1). Future work should focus on increasing pasture measurement accuracy to potentially strengthen the predictive ability of sensor-based behaviours, as this was likely a limitation of our study (see Fig. 1). Doing so may also improve the models for other relationships; for instance prediction of pasture disappearance, a proxy for animal intake, which is challenged by requiring estimates of both pre- and post-grazing pasture mass.

There was a range in predictive ability between sensors and animal behaviours. As an individual behaviour, rumination time had the strongest relationship with pasture parameters. Following a grazing bout, cows must reduce the particle size of consumed feed by regurgitating and chewing it (ruminating). Consequently, it is logical that this behaviour explains more variation in post-grazing residual, compared to eating time or activity. The latter could be influenced by several factors, including pasture characteristics; for instance, we observed longer grazing times in the late summer period, which coincided with less ryegrass leaf and could have required more effort to eat. However, the inclusion of eating time (if the sensor provided it) did increase the predictive ability of the model compared with using rumination time alone, likely due to its direct link to post-grazing residual (e.g., more eating time, less pasture left). Eating time is known to be affected by reduced feed allocation, as well as the length of the feed, while the digestibility (e.g., neutral detergent fibre) impacts rumination (Beauchemin, 2018). A large portion of rumination behaviour occurs at night (Gregorini et al., 2012; Pollock et al., 2022; Iqbal et al., 2023). Thus, it is logical that including duration in the paddock or pasture disappearance curves did not improve model performance; the majority of rumination would not be occurring when the cows were outside the paddock, nor coincide with changes in pasture height (disappearance curve). The paddock duration result has practical relevance since many sensors lack location monitoring, and our results indicate it is not required for the purpose of predicting pasture mass on a per ha basis.

Including pasture quality in the model had a modest effect on model performance, particularly for eShepherd and IceQube. Both these sensors did not report rumination time and had poorer predictive ability (Fig. 5), consequently, the improvement was likely due to the correlations between pasture quality and rumination time (Fig. 3). However, the performance remained below that of the sensors that reported rumination time. It is challenging to collect pasture quality data in near real-time, limiting the use of the approach.

There were strong correlations between the group level rumination time reported by different sensors as well as similar direction and magnitudes of their model coefficients; however, their outputs did differ (sometimes considerably). For instance, on average, compared to the spring period, CowManager and AfiCollarV2 sensors logged 26 min and 97 min more eating time in the summer, while rumination time reduced by 75 min and 100 min, respectively. For the same behaviour there were differences in these group daily values between sensors ranging between 20 and nearly 80 min. The variation between the sensors we used likely relates to a combination of the data recording method, how the device is secured (e.g., ear tag, neck collar, leg band, internal dwelling), and how the proprietary algorithms interpret the data (these algorithms can also change due to software upgrades as evidenced with the AfiCollar sensor). Furthermore, to our knowledge, there has not been a systematic comparison of how the various manufacturers' algorithms cope with changes in the pasture type available at different types of year, e.g., longer, fast growing swards in late spring versus shorter, tougher herbage in late summer (Beauchemin, 2018). It is possible that due to the changes in the way the cow consumes these forage types (e.g., pulling more with the tongue), the algorithms may run into classification issues (e.g., feeding being confused with rumination and vice versa). Regardless of potential classification differences, similarly-named behaviours from various sensors proved to be equally useful for predicting pasture parameters. However, it does raise the question of whether any filtering criteria (such as minimum or maximum values) should be applied at an animal level prior to determining group averages for the prediction of pasture mass.

Further attempts to improve model performance in our study were generally unsuccessful, except for the inclusion of pasture quality for sensors that did not report rumination time, as previously discussed. The inclusion of animal parity as a model factor did not improve the models' predictive ability, nor did the inclusion of behaviours from multiple sensors. This is not surprising due to collinearity of the measures. Nonetheless, it is useful to know because if accuracy required multiple sensors, it would increase cost and complexity and reduce the likelihood of adoption by farmers.

Machine learning methods performed slightly better in our study compared to traditional linear models, however we believe our training and test datasets were too small for these models to accurately capture all possible patterns of animal behaviour and pasture availability. There is a risk of overfitting in machine learning models when trained on a limited dataset (Ying, 2019), and though we employed cross validation, overfitting remains a possibility.

Variability in the post-grazing models' predictive ability could be at least partially attributed to differences in the ability of individual animal to cope with under allocation of pasture. Iqbal et al. (2022) demonstrated that up to 20 % of the variation in daily behaviours was driven by individual cow differences. While our study's use of averages masked the extremes, it is likely that pasture depletion was experienced differently by different animals. For example, average and maximum rumination times in Period 1 were similar to that reported by Neave et al. (2021), who used CowManager sensors during a similar season as our study. However, we recorded lower minimum rumination times (e.g., more than 2 h less/day). While the study by Neave et al. (2021) aimed to provide consistent pasture allocation (between 19 and 20 kg DM/d per cow), it highlights that the under allocation in our study likely prevented some animals from getting an opportunity to ingest as much feed as their conspecifics (e.g., slower eating rate, subordinates being forced on to already grazed sections), thus impacting their rumination time negatively. Averaging of the data is necessary for the purposes of estimating group-based pasture allocation measures, but this raises the question about what the under allocation threshold should be to avoid compromising individual animal welfare on-farm.

There are practical considerations for using on-animal sensor data for estimating post-grazing residual (kg DM/ha) as the best predicted pasture parameter. For instance, due to cows being crepuscular in nature (Iqbal et al., 2023), and offering fresh pasture every 24 h in our study, we created our model using daily behaviour; however, many pasture-based herds graze multiple paddocks within a day (e.g., a new paddock every 12 h). Thus, it could prove challenging to predict post-grazing residual for each paddock. Due to this, as well as day-to-day variabilities common to on-farm environments, including feed supplementation, the practical relevance of our models for farm management may be limited to indicating the general trend of post-grazing residual.

Despite the limitations outlined, this approach provides a near real-time, objective, measure of post-grazing residual that may have value to farm managers over existing subjective visual assessment or time-consuming use of RPM. Further, the root-mean-square errors of this approach, using on-animal sensors, compares favourably to those reported by satellite and aerial vehicle for estimating pasture mass (Gargiulo et al., 2023). Future work should focus on collecting much larger datasets, including more accurate measures of pasture mass, with additional variables captured at different resolutions, to allow non-linear machine learning approaches to be applied, potentially addressing some of the limitations we faced. Further, research is needed that provides this near real-time data to farmers and assesses the potential value by monitoring their decision making, cognitive load, and well-being.

## 5. Conclusion

This proof-of-concept experiment has demonstrated that data from individual on-animal sensors can be used to predict post-grazing pasture mass (kg DM/ha), a useful metric for grazing management. The most important animal behaviour was rumination time, and the predictive ability of sensors that included this behaviour was considerably better than those that did not. Sensors reporting similar behaviours (e.g., feeding, rumination) were strongly correlated, however, differences existed in the daily group averages each presented. The importance of rumination and its diurnal nature likely explains why including data at less than 24 h resolution (pasture disappearance curves) did not improve model performance. This, as well as day to day variability due to variation likely caused by individual cow differences or weather, could limit the practical application of this for daily or sub-daily grazing management. However, given its near real-time nature, low effort, and objectivity it may still provide value; the latter must be determined by working with farmers to evaluate how providing this data affects their decision making.

## CRediT authorship contribution statement

**J.P. Edwards:** Conceptualization, Methodology, Software, Resources, Data curation, Writing – original draft, Writing – reviewing & editing, Visualization, Supervision, Project administration. **M. Qasim:** Software, Validation, Formal analysis, Data curation, Visualization. **R. H. Bryant:** Methodology, Resources. **C. Thomas:** Methodology, Investigation, Resources, Data curation. **C. Wright-Watson:** Investigation. **G. Zobel:** Writing – reviewing & editing, Visualization. **M.B. Neal:** Conceptualization, Methodology. **C.R. Eastwood:** Conceptualization, Methodology, Writing – reviewing & editing.

## Declaration of competing interest

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

## Data availability

Data will be made available on request.

## Acknowledgements

This work was supported by the New Zealand Ministry of Business and Innovation and Employment's Strategic Science Investment Fund within the AgResearch Ltd. research programme 'The New Zealand Bioeconomy in the Digital Age' (contract A27096) and the dairy farmers of New Zealand through DairyNZ Inc (contract TW2101). We would like to thank the farm staff at the Ashley Dene Research and Development Station (Lincoln University) for herd management, A. Arazi (AfiMilk) for extracting AfiCollar data, and A Zipsin (Gallagher Group Ltd) for arranging installation and extraction of eShepherd data. We would also like to thank the farmers and rural professionals that participated in a co-design workshop that determined the research question addressed in this work. Finally, we acknowledge the thoughtful reviewer comments that helped refine our manuscript.

## References

AFRC (1993) 'Energy and Protein Requirements of Ruminants.' (CAB INTERNATIONAL: Wallingford, UK).

Augustine, D.J., Raynor, E.J., Kearney, S.P., Derner, J.D., 2022. Can measurements of foraging behaviour predict variation in weight gains of free-ranging cattle? Animal Production Science 62, 926–936. https://doi.org/10.1071/AN21560.

Beauchemin, K.A., 2018. Invited review: current perspectives on eating and rumination activity in dairy cows. Journal of Dairy Science 101, 4762–4784. https://doi.org/10.3168/jds.2017-13706.

Beukes, P.C., McCarthy, S., Wims, C.M., Gregorini, P., Romera, A.J., 2019. Regular estimates of herbage mass can improve profitability of pasture-based dairy systems. Animal Production Science 59, 359–367. https://doi.org/10.1071/AN17166.

Chilibroste, P., Gibb, M.J., Soca, P., Mattiauda, D.A., 2015. Behavioural adaptation of grazing dairy cows to changes in feeding management: do they follow a predictable pattern? Animal Production Science 55, 328–338. https://doi.org/10.1071/AN14484.

Clark, C.E.F., Lyons, N.A., Millapan, L., Talukder, S., Cronin, G.M., Kerrisk, K.L., Garcia, S.C., 2015. Rumination and activity levels as predictors of calving for dairy cows. Animal 9, 691–695. https://doi.org/10.1017/S1751731114003127.

Dela Rue, B.T., Eastwood, C.R., Edwards, J.P., Cuthbert, S., 2020. New Zealand dairy farmers preference investments in automation technology over decision-support technology. Animal Production Science 60, 133–137. https://doi.org/10.1071/AN18566.

Eastwood, C.R., Dela Rue, B.T., 2017. Identification of operational performance attributes for pasture measuring devices. Journal of New Zealand Grasslands 79, 217–222. https://doi.org/10.33584/jnzg.2017.79.532.

Eastwood, C.R., Dela Rue, B.T., Gray, D.I., 2017. Using a 'network of practice' approach to match grazing decision-support system design with farmer practice. Animal Production Science 57, 1536–1542. https://doi.org/10.1071/AN16465.

Eastwood, C., Dela Rue, B., Kerslake, J., 2020. Developing an approach to assess farmer perceptions of the value of pasture assessment technologies. Grass and Forage Science 75, 474–485. https://doi.org/10.1111/gfs.12504.

Eastwood, C.R., Dela Rue, B.T., Edwards, J.P., Jago, J.G., 2022. Responsible robotics design–a systems approach to developing design guides for robotics in pasture-grazed dairy farming. Frontiers in Robotics and AI. https://doi.org/10.3389/frobt.2022.914850.

Fountas, S., Wulfsohn, D., Blackmore, B.S., Jacobsen, H.L., Pedersen, S.M., 2006. A model of decision-making and information flows for information-intensive agriculture. Agricultural Systems 87, 192–210. https://doi.org/10.1016/j.agsy.2004.12.003.

Fulkerson, W.J., McKean, K., Nandra, K.S., Barchia, I.M., 2005. Benefits of accurately allocating feed on a daily basis to dairy cows grazing pasture. Australian Journal of Experimental Agriculture 45, 331–336. https://doi.org/10.1071/EA03109.

Ganche, E., Delaby, L., O'Donovan, M., Boland, T.M., Galvin, N., Kennedy, E., 2013. Post-grazing sward height imposed during the first 10 weeks of lactation: influence on early and total lactation dairy cow production, and spring and annual sward characteristics. Livestock Science 157, 299–311. https://doi.org/10.1016/j.livsci.2013.08.001.

Gargiulo, J.I., Lyons, N.A., Masia, F., Beale, P., Insua, J.R., Correa-Luna, M., Garcia, S.C., 2023. Comparison of ground-based, unmanned aerial vehicles and satellite remote sensing Technologies for Monitoring Pasture Biomass on dairy farms. Remote Sensing 15, 2752. https://doi.org/10.3390/rs15112752.

Glassey, C.B., Rawnsley, R.P., Macdonald, K.A., 2010. The emergence, development and effectiveness of decision rules for pasture based dairy systems. In: Proceedings of the 4th Australasian Dairy Science Symposium'. Caxton Press, Christchurch, Lincoln, New Zealand, pp. 199–209.

Greenwood, P.L., Paull, D.R., et al., 2017. Use of sensor-determined behaviours to develop algorithms for pasture intake by individual grazing cattle. Crop and Pasture Science 68, 1091–1099. https://doi.org/10.1071/CP16383.

Gregorini, P., Clark, C.E.F., Jago, J.G., Glassey, C.B., McLeod, K.L.M., Romera, A.J., 2009. Restricting time at pasture: effects on dairy cow herbage intake, foraging behavior, hunger-related hormones, and metabolite concentration during the first grazing session. Journal of Dairy Science 92, 4572–4580. https://doi.org/10.3168/jds.2009-2322.

Gregorini, P., DelaRue, B., McLeod, K., Clark, C.E.F., Glassey, C.B., Jago, J., 2012. Rumination behavior of grazing dairy cows in response to restricted time at pasture. Livestock Science 146, 95–98. https://doi.org/10.1016/j.livsci.2012.02.020.

Gregorini, P., Villalba, J.J., Chilibroste, P., Provenza, F.D., 2017. Grazing management: setting the table, designing the menu and influencing the diner. Animal Production Science 57, 1248–1268. https://doi.org/10.1071/AN16637.

Iqbal, M.W., Draganova, I., Morel, P.C.H., Morris, S.T., 2022. Factors affecting grazing and rumination behaviours of dairy cows in a pasture-based system in New Zealand. Animals 12, 3323. https://doi.org/10.3390/ani12233323.

Iqbal, M.W., Draganova, I., Henry Morel, P.C., Todd Morris, S., 2023. Variations in the 24 h temporal patterns and time budgets of grazing, rumination, and idling behaviors in grazing dairy cows in a New Zealand system. Journal of Animal Science 101. https://doi.org/10.1093/jas/skad038.

Kennedy, E., McEvoy, M., Murphy, J.P., O'Donovan, M., 2009. Effect of restricted access time to pasture on dairy cow milk production, grazing behavior, and dry matter intake. Journal of Dairy Science 92, 168–176. https://doi.org/10.3168/jds.2008-1091.

Kuhn, M., 2008. Building predictive models in R using the caret package. Journal of Statistical Software 28, 1–26. https://doi.org/10.18637/jss.v028.i05.

Lile, J.A., Blackwell, M.B., Thomson, N.A., Penno, J.W., Macdonald, K.A., Nicholas, P.K., Lancaster, J.A.S., Coulter, M., 2001. Practical use of the rising plate meter (RPM) on New Zealand dairy farms. Proceedings of the New Zealand Grassland Association 63, 159–164. https://doi.org/10.33584/jnzg.2001.63.2425.

Macdonald, K.A., Penno, J.W., Lancaster, J.A.S., Roche, J.R., 2008. Effect of stocking rate on pasture production, Milk production, and reproduction of dairy cows in pasture-based systems. Journal of Dairy Science 91, 2151–2163. https://doi.org/10.3168/jds.2007-0630.

Macdonald, K.A., Beca, D., Penno, J.W., Lancaster, J.A.S., Roche, J.R., 2011. Short communication: Effect of stocking rate on the economics of pasture-based dairy farms. Journal of Dairy Science 94, 2581–2586. https://doi.org/10.3168/jds.2010-3688.

McCarthy, S., Hirst, C., Donaghy, D., Gray, D., Wood, B., 2014. Opportunities to improve grazing management. Proceedings of the New Zealand Grassland Association 76, 75–79. https://doi.org/10.33584/jnzg.2014.76.2971.

McCown, R.L., Carberry, P.S., Dalgliesh, N.P., Foale, M.A., Hochman, Z., 2012. Farmers use intuition to reinvent analytic decision support for managing seasonal climatic variability. Agricultural Systems 106, 33–45. https://doi.org/10.1016/j.agsy.2011.10.005.

Mottram, T., 2016. Animal board invited review: precision livestock farming for dairy cows with a focus on oestrus detection. Bioscience 10, 1575–1584. https://doi.org/10.1017/S1751731115002517.

Murphy, D.J., OB, B., Hennessy, D., Hurley, M., Murphy, M.D., 2021. Evaluation of the precision of the rising plate meter for measuring compressed sward height on heterogeneous grassland swards. Precision Agriculture 22, 922–946. https://doi.org/10.1007/s11119-020-09765-9.

Neal, M., Roche, J.R., 2020. Profitable and resilient pasture-based dairy farm businesses in New Zealand. Animal Production Science 60, 169–174. https://doi.org/10.1071/AN18572.

Neal, M.B., Woodward, S.J.R., Dela Rue, B.T., 2019. Identifying the pasture potential for New Zealand dairy farms. Journal of New Zealand Grasslands 81, 235–240. https://doi.org/10.33584/jnzg.2019.81.405.

Neave, H.W., Edwards, J.P., Thoday, H., Saunders, K., Zobel, G., Webster, J.R., 2021. Do walking distance and time away from the paddock influence daily behaviour patterns and Milk yield of grazing dairy cows? Animals 11. https://doi.org/10.3390/ani11102903.

Neave, H.W., Schütz, K.E., Dalley, D.E., 2022a. Behavior of dairy cows managed outdoors in winter: effects of weather and paddock soil conditions. Journal of Dairy Science 105, 8298–8315. https://doi.org/10.3168/jds.2022-21819.

Neave, H.W., Zobel, G., Thoday, H., Saunders, K., Edwards, J.P., Webster, J., 2022b. Toward on-farm measurement of personality traits and their relationships to behavior and productivity of grazing dairy cattle. Journal of Dairy Science 105, 6055–6069. https://doi.org/10.3168/jds.2021-21249.

Nicol, A.M., Brookes, I.M., 2007. The metabolisable energy requirements of grazing livestock. In: Rattray, P.V., Brookes, I.M., Nicol, A.M. (Eds.), Pasture and Supplements for Grazing Animals. The New Zealand Society of Animal Production, Hamilton, New Zealand, pp. 151–172.

Öhlmér, B., Olson, K., Brehmer, B., 1998. Understanding farmers' decision making processes and improving managerial assistance. Agricultural Economics 18, 273–290. https://doi.org/10.1016/S0169-5150(97)00052-2.

O'Leary, N.W., Byrne, D.T., O'Connor, A.H., Shalloo, L., 2020. *Invited review:* cattle lameness detection with accelerometers. Journal of Dairy Science 103, 3895–3911. https://doi.org/10.3168/jds.2019-17123.

Pereira, G.M., Heins, B.J., Endres, M.I., 2018. Technical note: validation of an ear-tag accelerometer sensor to determine rumination, eating, and activity behaviors of grazing dairy cattle. Journal of Dairy Science 101, 2492–2495. https://doi.org/10.3168/jds.2016-12534.

Pérez-Prieto, L.A., Delagarde, R., 2013. Meta-analysis of the effect of pasture allowance on pasture intake, milk production, and grazing behavior of dairy cows grazing temperate grasslands. Journal of Dairy Science 96, 6671–6689. https://doi.org/10.3168/jds.2013-6964.

Pollock, J.G., Gordon, A.W., Huson, K.M., McConnell, D.A., 2022. The effect of frequency of fresh pasture allocation on the feeding behaviour of high production dairy cows. Animals 12, 243. https://doi.org/10.3390/ani12030243.

Refaeilzadeh, P., Tang, L., Liu, H., 2009. Cross-validation. In: Liu, L., ÖZsu, M.T. (Eds.), Encyclopedia of Database Systems. Springer US, Boston, MA, pp. 532–538.

Rennie, G.M., King, W.M.C.G., Puha, M.R., Dalley, D.E., Dynes, R.A., Upsdell, M.P., 2009. Calibration of the C-DAX rapid pasturemeter and the rising plate meter for kikuyu-based northland dairy pastures. Proceedings of the New Zealand Grassland Association 71, 49–55. https://doi.org/10.33584/jnzg.2009.71.2779.

Roche, J.R., Friggens, N.C., Kay, J.K., Fisher, M.W., Stafford, K.J., Berry, D.P., 2009. *Invited review:* body condition score and its association with dairy cow productivity, health, and welfare. Journal of Dairy Science 92, 5769–5801. https://doi.org/10.3168/jds.2009-2431.

Rombach, M., Münger, A., Niederhauser, J., Südekum, K.H., Schori, F., 2018. Evaluation and validation of an automatic jaw movement recorder (RumiWatch) for ingestive and rumination behaviors of dairy cows during grazing and supplementation. Journal of Dairy Science 101, 2463–2475. https://doi.org/10.3168/jds.2016-12305.

Thomson, N.A., Upsdell, M.P., et al., 2001. Development and evaluation of a standardised means for estimating herbagemass of dairy pastures using the rising plate meter. Proceedings of the New Zealand Grassland Association 63, 149–157. https://doi.org/10.33584/jnzg.2001.63.2439.

Ying, X., 2019. An overview of overfitting and its solutions. Journal of Physics: Conference Series 1168, 022022. https://doi.org/10.1088/1742-6596/1168/2/022022.