Assessing the validity of sensor-based predictions of post-grazing residual in dairy systems

Wayne A. HOFMANN[1*], J. Paul EDWARDS[2], Mark B. NEAL[1] and Simon J. R. WOODWARD[1]

[1] *DairyNZ Ltd, Private Bag 3221, Hamilton 3240, New Zealand*
[2] *DairyNZ Ltd, PO Box 85066, Lincoln, 7647, New Zealand*
*Corresponding author: Wayne.Hofmann@dairynz.co.nz

Abstract

Knowledge of post-grazing residuals are crucial for dairy farmers to adjust feed inputs and optimise pasture utilisation. However, many farmers rely on subjective methods, like visual assessment, to make grazing decisions. This case study evaluation applied a predictive model for post-grazing residual, based on previous research, to two farms: a research dairy farm with smaXtec rumen boluses divided into three farmlets (alternative pastures, current and low emissions) and a commercial dairy farm with cows equipped with AfiCollars. The aim was to assess the model's performance in an uncontrolled environment. There was some alignment between the predicted post-grazing residuals from the sensor-based model and rising plate meter data. However, the model's explanatory ability was poor, with R^2 values calculated as the coefficient of determination ranging from -1.31 for the alternative pastures farmlet to 0.05 for the current farmlet and 0.15 for the low emissions farmlet. On the commercial farm, the R^2 was -1.24. While previous studies have demonstrated the potential of predicting pasture residuals from animal sensors, our study identified some challenges that would need to be overcome for broader application, including accounting for variations in on-farm management practices (e.g., supplement usage, frequency of pasture allocation, and mulching) and pasture species diversity. Given the infancy of this approach, further research is necessary to refine the predictive capabilities and clarify the specific contexts where its use could benefit New Zealand farmers.

Keywords: individual animal monitoring, pasture management, rotational grazing, precision agriculture, predictive models

Introduction

Optimal pasture management, including accurate estimation of herbage yield, plays a crucial role in the production of milksolids and the overall profitability of dairy farms. Pasture growth follows a seasonal pattern in temperate regions like New Zealand, making it the primary source of feed for dairy cattle (Holmes et al. 2002; Neal and Roche 2019) and providing the New Zealand dairy industry a competitive edge on the global stage due to its low-cost nature (Neal 2021). However, pasture growth is highly variable within and between years due to factors such as pests, species mix, rainfall, temperature, soil nutrient status and management (Keller et al. 2021). Such fluctuations in inter-annual variability in pasture herbage accumulation introduce significant complexity to grazing management strategies (Chapman et al. 2013).

For dairy farmers utilising rotational grazing, knowledge of post-grazing residuals, which reflect the animals' feeding status, is vital. This knowledge, in conjunction with other farm data (e.g., average pasture cover and feed wedge), helps inform farm decisions such as adjusting feed supply (e.g., daily pasture allowance and supplement usage) to prioritise the utilisation of low-cost, high-quality pasture, leading to cost savings and environmental sustainability (Rotz et al. 2020; Palma-Molina et al. 2023). Such strategies aim to maximise pasture utilisation, provide a constant feed allocation to maintain milk production, decrease dependence on imported feeds, and uphold farm profitability by optimising animal and pasture performance (Holmes et al. 2002; Fulkerson et al. 2005).

Maintaining post-grazing residuals at the appropriate level for ryegrass and white clover pastures, which Barenbrug (2024) described as 5 cm or 1500 kg DM/ha in dairy systems, is desirable for several reasons, including maximising pasture utilisation, retaining pasture quality for subsequent grazings, and maintaining pasture in an actively growing state (Chapman et al. 2012; Roche et al. 2017). A lower post-grazing residual will decrease subsequent pasture regrowth and total pasture production and may reduce pasture persistence, while a higher residual will reduce pasture utilisation and subsequent pasture quality, lowering animal performance (McCarthy et al. 2014; Leddin et al. 2023; Barenbrug 2024).

Many farmers do not estimate pre or post-grazing pasture mass due to the inconvenience and the time required to measure pasture mass using currently available methods such as the rising plate meter (RPM) (Anderson and McNaughton 2018). Additionally, the perceived inaccuracy of the RPM due to the number of calibration equations available (e.g., variations

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by season, region and pasture species) to convert the RPM readings into a measure of herbage mass further discourages its use (Lile et al. 2001). Previous studies have found visual estimation of herbage mass by trained observers to be more accurate than using a RPM (L'Huillier and Thomson 1988; O'Donovan et al. 2002). Due to these disadvantages of the RPM, many farmers rely on subjective measures (e.g., visual assessment), intuition, and experience from previous seasons to make farm grazing and feeding decisions (Leddin et al. 2023). Incorporating measured pre- and post-grazing data regularly (e.g., weekly) in such decisions with other farm data can facilitate maintaining optimal animal feeding levels, pasture utilisation, and pasture quality by enabling early detection of under or overfeeding situations and pasture surpluses or deficits, therefore allowing for timely management interventions.

Since 2018, New Zealand dairy farmers have increasingly invested in animal sensors, including collars and internal cattle boluses, as Dela Rue and Eastwood (2023) reported. In their five-yearly survey of 500 farmers, approximately 18% of respondents had incorporated animal sensors into their systems, up significantly from less than 3% in the previous surveys in 2013 and 2018. Today, various animal sensors are available that can estimate a range of animal behaviours, including rumination and grazing behaviour, through proprietary algorithms.

Edwards et al. (2024) demonstrated the potential for automatic estimation of post-grazing residual in near real-time using data from animal sensors. This pilot study, at the Ashley Dene Research and Development Station in Springston, Canterbury, New Zealand, involved four groups of 25 crossbred cows assigned to four different feeding levels (80-120% of daily energy requirements) and being equipped with various animal sensors, including smaXtec boluses and AfiCollars. A predictive model using the sensor data and calibrated RPM measurements of post-grazing pasture mass showed R^2 values of 0.51 for smaXtec and 0.57 for AfiCollar. The best-predicted pasture metric was post-grazing residual (kg DM/ha), with a root mean squared error (RMSE) around 130 kg DM/ha (e.g., AfiCollar 126 kg DM/ha, smaXtec 133 kg DM/ha). Since this data is available in near real-time and requires minimal effort, combining sensor data with other pasture assessment measures (e.g., visual or RPM) may help guide pasture management and dairy herd feeding decisions on-farm.

The current study adopted a case study approach on two farms, leveraging pre-existing data to assess the effectiveness of the predictive models of post-grazing residual proposed by Edwards et al. (2024). The study specifically aimed to determine whether the predicted post-grazing residuals, based on animal sensor data, aligned with the post-grazing residuals estimated from RPM farm walk data. This comparison was conducted on a research farm over a complete lactation and a commercial farm over a partial lactation. This evaluation was crucial in understanding the reliability and practicality of these predictive models in estimating post-grazing residuals under real-world farm conditions instead of research conditions where the predictive equations were developed, potentially guiding refinements if necessary for sensor developers or animal researchers.

Materials and Methods

Experimental sites and set-up

Cow sensor and aligned RPM data were obtained from two studies during the 2021/2022 season. The first farm was the Northland Agricultural Research Farm (NARF) in Dargaville, New Zealand, which utilised the smaXtec bolus system, while the second farm was a commercial farm situated in Canterbury, New Zealand, utilising the AfiCollar system. The study was approved by the Lincoln University Animal Ethics Committee (AEC 2021-12).

NARF: smaXtec bolus system

The smaXtec system (smaXtec, animal care GmbH, Graz, Austria) comprises an on-farm plug-and-play base station that utilises the LoRa network and an internal cattle bolus. Weighing 210 g and measuring 105 mm × 35 mm (L × W), the bolus has an estimated life of 5 years based on battery capacity. Following dosing, the device enters the reticulum, the second compartment of the ruminant stomach. It continuously reports a range of health metrics at 10-minute intervals, including animal temperature, drinking activity, and rumination and activity time (e.g., walking), using an accelerometer. The on-farm base station, positioned at a suitable location on-farm (e.g. cowshed), uses the cellular network to read the bolus data and upload it to the smaXtec cloud, where it is permanently saved and accessible anywhere. Once uploaded, the data is analysed and made available for viewing, and where on-farm action is required, data alerts are sent to registered users (smaXtec animal care GmbH 2024).

Data from the smaXtec system was obtained at NARF (-35.943° S, 173.841° E), an 82-hectare dairy farm, between August 2021 and May 2022 (boluses had previously been inserted in December 2020). The farm was subdivided into three distinct farmlets (low emissions, current, and alternative pastures), each evaluated separately. The farmlets were established in June 2021 as part of the 4-year Future Farm Systems Trial (Northland Dairy Development Trust 2024). Each farmlet was approximately 27 ha with the low emissions, and the current farmlet featuring kikuyu (*Pennisetum* *clandestinum*) and Italian ryegrass (*Lolium multiflorum*) pastures. By contrast, the alternative pastures farmlet featured a diverse range of pasture species, including tall fescue (*Festuca arundinacea*), cocksfoot (*Dactylis glomerata*), plantain (*Plantago lanceolata*) and chicory (*Cichorium intybus*).

Over the study period, a mixture of twice-daily and once-daily milking was used, and new pasture was allocated after each milking. Herd sizes were 59 cows for the low-emissions farmlet, a low-stocked farmlet aimed at reducing greenhouse gas emissions, 86 cows for the farmlet operating under a typical Northland farming system (current farmlet) and 86 cows for the alternative pasture species farmlet. A total of 43 cows from the low-emissions farmlet, 61 cows from the current farmlet and 54 cows from the alternative pastures farmlet had smaXtec bolus sensors, representing 63-73% of the milking herd in each farmlet. All herds contained a mixture of breeds. The age breakdown of the animals with boluses in each farmlet was approximately 27.5% 3-year-old cows, 72% 4-8-year-old cows and 0.5% 9+-year-old cows.

Pasture data was obtained from a weekly farm walk conducted by the farm manager using a RPM to take at least 50 readings over a cross-section of each paddock. The RPM is a tool consisting of a steel plate and a 1 m shaft, and when lowered to ground level, the steel plate rises relative to sward height, providing an estimate of the compressed sward height (CSH) (McSweeney et al. 2019). To convert CSH into an estimate of the available kilograms of dry matter, the standard RPM formula (CSH × 140 + 500) was used with each click equal to approximately 0.5 cm compressed sward height (Lile et al. 2001; DairyNZ 2023). This equation provides the best fit in most situations (DairyNZ 2023). This information, along with other farm data such as daily cow numbers per farmlet and supplements fed, was recorded by NARF staff and used to explore the relationship between estimated post-grazing residuals based on the RPM data and predicted post-grazing residuals based on on-animal sensor data.

Commercial farm: AfiCollar system

The AfiCollar (Afimilk Ltd, Kibbutz Afikim, Israel) system comprises an animal sensor on a cow collar and an on-farm reader. Each collar weighs approximately 655 g, including the counterweight with the sensor placed on the left side of a cow's neck. Featuring an onboard accelerometer, the device can distinguish between animal behaviours, such as rumination and eating time, based on the patterns of the animal's head movements (Leso et al. 2021). An on-farm reader is also installed at a suitable location (e.g. cowshed), enabling wireless data transmission from the collars to the reader before uploading it to the herd management software, AfiFarm, for user access.

Data was obtained between December 2021 and May 2022 from a commercial 85-hectare dairy farm at Hororata, Canterbury, New Zealand. The farm milked approximately 230 mixed-breed cows and implemented various milking regimes throughout the study, including twice daily, three times in two days (3-in-2 milking), and once daily. One hundred cows, representing ~43% of the milking herd, were fitted with the AfiCollar system for the duration of the study.

In parallel, approximately every 3 weeks, a DairyNZ research technician conducted farm walks using a RPM, taking at least 50 readings per paddock in a zig-zag pattern. As per NARF, an estimate of available dry matter was calculated using the standard plate meter formula (CSH × 140 + 500). Other collected records included paddocks grazed and supplements fed.

Data analysis

Utilising proprietary algorithms, the smaXtec and AfiCollar sensors classify the animal movement data for each cow into various categories, such as activity time (e.g., walking), rumination time and eating time (Edwards et al. 2024). After this initial classification, the data was retrieved from the respective manufacturers' data portals. In this study, the smaXtec system provided rumination time as a 24-hour rolling average in seconds. The activity data was calculated hourly based on each cow's movement activity (e.g., walking or jumping up) within each hour and provided as an activity index ranging from 0 (no activity) to 100 (high activity). For each cow, the midnight rumination value was converted from seconds to minutes to calculate the total time spent ruminating during each 24 hours, while activity time was summed over each 24 hours (midnight to midnight). By contrast, using hour blocks of the day, the AfiCollar system records the total seconds spent on each activity (e.g., rumination or eating). These values were converted to minutes per hour and then summed to calculate the total minutes spent eating or ruminating within each 24 hours. Any missing data due to sensor failure or faults were excluded from further analysis.

The predictive equations from Edwards et al. (2024) were applied to the group average daily cow behavioural classifications to estimate the post-grazing residual. The equations were developed on a daily basis because animals were managed using 24-hour grazing. However, because pasture data was only available at a maximum of weekly, the mean post-grazing residual estimated using the sensor data was averaged across the week to align the sensor models. Equation A below was used for the smaXtec data, and Equation B was used for the AfiCollar data.

Equation A: Post-grazing residual (kg DM/day) = 154.38 + 3.01 × rumination time (minutes/day) + 0.42 × sum daily activity index (Edwards et al. 2024)

Equation B: Post-grazing residual (kg DM/day) = 1017.65 + 1.88 × rumination time (minutes/day) - 0.06 × eating time (minutes/day) (Edwards et al. 2024)

As post-grazing residuals were not directly measured on either farm due to the cost of collecting this at the required frequency, the "observed" pasture residual was estimated as the average of the six lowest paddocks at each farm walk (i.e., we assumed these were the most recently grazed) based on RPM data as a proxy for post-grazing residual, acknowledging that it is likely there would have been some pasture regrowth depending on the season after 2-3 days. We then applied a regression analysis to compare how well the predicted pasture residual from the sensor models aligned with this observed pasture residual. R^2 values were then calculated as the coefficient of determination of the model prediction against the 1:1 line.

$$R^2 = 1 - \frac{\sum_i (observed_i - predicted_i)^2}{\sum_i (observed_i - mean(observed))^2}$$

All analyses were performed using R Statistical Software (v4.2.1; R Core Team 2022), RStudio (v2023.06.2; Posit Team 2023) and the most recent libraries (e.g., tidyverse, lubridate, ggpmisc) at the time of writing. For the smaXtec data, all dates and times were initially recorded in Coordinated Universal Time (UTC), and these were subsequently converted to New Zealand Standard Time (NZST) or New Zealand Daylight Savings Time (NZDT), depending on the time of year, using the R lubridate package to enable the analysis to take place (v1.9.3; Grolemund and Wickham 2011). This step was not required for the AfiCollar data as the data correctly displayed the date and time as either NZST or NZDT to account for daylight savings.

Results and Discussion

The performance of the predictive equations for calculating post-grazing residuals using either smaXtec or AfiCollar data is shown in Figure 1. Coefficient of determination (R^2) values were all poor, ranging from -1.31 for the alternative pastures farmlet to 0.05 for the current farmlet and 0.15 for the low-emissions farmlet using the smaXtec data. The predictive performance of the equation using AfiCollar data was also poor, producing a coefficient of determination (R^2) value of -1.24. Since our model was created from a different dataset, it may have an $R^2 <0$ when tested on new data. An $R^2 <0$ means that the model is worse at predicting the data than simply using the mean value of the data. However, since the mean value of the data is not available *a priori*, the model may still have value.

At NARF, the farmlet where the predictive equation had the best alignment between predicted and observed residuals was the low emissions farmlet based on kikuyu and ryegrass-based pastures and limited supplement used compared with the other farmlets (Figure 2). This farmlet aligns best with the conditions of the original study by Edwards et al. (2024), where no supplements were used. The predictive equation performed the worst in the alternative pasture farmlet, likely due to the original model being developed for traditional dairy pastures consisting of perennial ryegrass (*Lolium perenne*) and white clover (*Trifolium repens*). A previous study by Hendriks et al. (2016) compared ryegrass and tall fescue drymatter yields using a calibrated RPM and found no difference in pre- and post-grazing measurements between the two species. Consequently, they used a single calibration equation: the standard plate meter formula (CSH × 140 + 500), the same equation as the current study. Similarly, Haultain et al. (2014) reported that the RPM showed comparable accuracy for first-year pure swards of chicory and plantain as it did for ryegrass-based pastures, though they noted that this accuracy might not hold in pastures with older chicory due to the development of large, woody reproductive stems. However, it is quite possible that the pasture composition affects grazing behaviour and, therefore, eating time/ruminating time/activity, consequently affecting the predicted residual.

Fulkerson and Slack (1993) have previously reported low accuracy in total dry matter estimation for kikuyu-based pastures when using the RPM. However, in a one-year study by Rennie et al. (2009) at NARF, a kikuyu effect could not be detected when using the RPM. Nevertheless, they suggested using different seasonal calibration equations for the RPM, specific to the region, rather than one equation applied across the season, as used in this study.

Figure 2 also highlights the influence that farm practices, such as feeding supplements and mulching of Kikuyu (March/early April), had on the ability of the equation using smaXtec data to predict the post-grazing residual. Notably, the predicted residual remains relatively stable when supplements were incorporated into the cow's diet to meet animal feed requirements. This is because the predictive equation is based on animal behaviours (e.g., rumination time). As animal intake is likely similar (e.g., supplement substituted for pasture or vice versa), the predictive equation could not

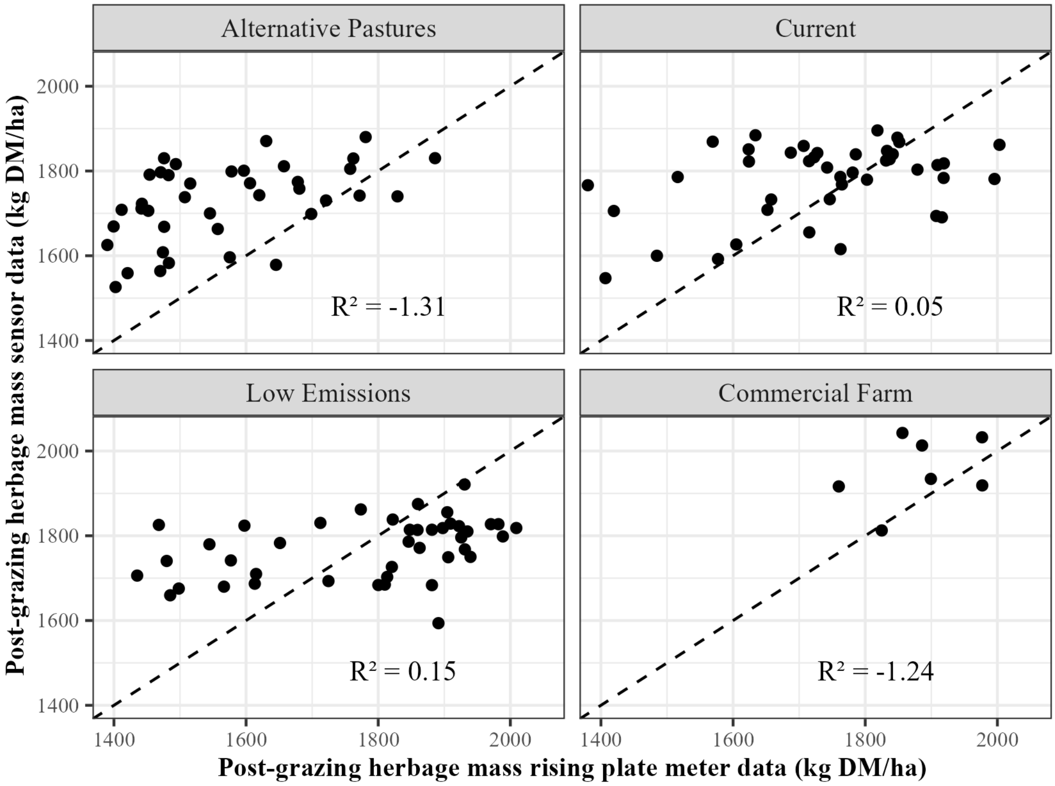

Figure 1 Comparison of the post-grazing mass estimate using the average of the six lowest paddocks at each farm walk (as measured by RPM) against the sensor predictive equations (smaXtec for alternative pastures, current and low emissions, and AfiCollar for the commercial farm). R^2 is the Coefficient of Determination of the model prediction. The dashed line is the 1:1 line.

distinguish if the dairy herd was potentially wasting pasture or supplement.

From late March 2022, there was a notable divergence between the predicted post-grazing residual and RPM estimates from farm walk data across two distinct farmlets: the low emissions and the current farm, both primarily kikuyu/ryegrass-based. This difference is likely attributed to the management practice of mulching kikuyu grass to aid in establishing Italian ryegrass for winter/early spring forage on these farmlets. For example, NARF staff estimate that the cows on these farmlets grazed to around 1650 kg DM/ha before mulching reduced the residual to approximately 1400 kg DM/ha.

Another factor that may have played a part in the results of this study using data obtained from the smaXtec system is the age of the animals involved. At NARF, there were no first-calving animals with boluses. Consequently, in the current study, the average age of cows with boluses was older than a typical herd. Given that the Edwards et al. (2024) predictive model for post-grazing residual was initially developed using cows blocked on age (2, 3, 4–8 and 9+ years old) to make a representative herd age structure and both rumination and activity time as components, this factor may have influenced the study's outcomes, as younger cows are likely to exhibit different grazing behaviours compared to older cows (Iqbal et al. 2022). For example, Iqbal et al. (2022) demonstrated that grazing and rumination times tend to decrease as cows mature.

In this study, both farms used supplementary feeds at various points during the season to meet animal feed requirements. However, as discussed earlier, the predictive equations were developed within a pasture-only system. Therefore, further research on farms that use animal sensors and feed supplements is required to refine the predictive equations and adapt them to farm systems incorporating supplementary feeds, as indicated by the findings of this study and that of Iqbal et al. (2022). Iqbal et al. (2022) observed significant changes in grazing and rumination behaviour based on AfiCollar data when supplementary feeds such as maize, turnips or dried distillers grain (DDG) were introduced to the cow's diet, with cows notably reducing their grazing and rumination times when supplemented, emphasising the importance of refining predictive models to account

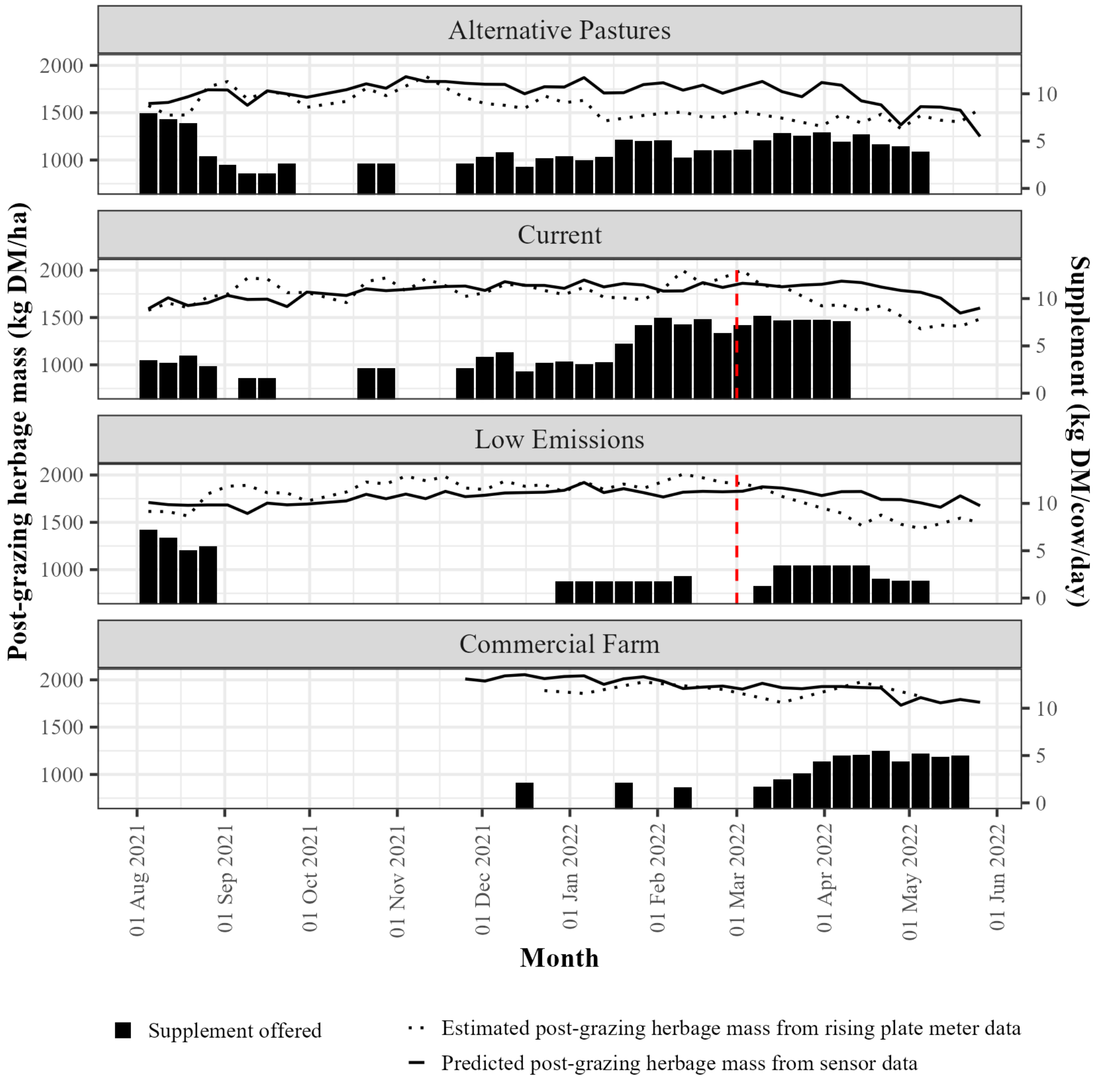

Figure 2 Predicted post-grazing mass using smaXtec data (NARF farmlets) and AfiCollar data (commercial farm) in relation to estimated post-grazing mass based on the average pasture mass of the six lowest paddocks at each farm walk (left-hand y-axis) and the amount of supplement offered (right-hand y-axis). The vertical dashed line indicates the start of on-farm mulching.

for this accurately in mixed feeding systems. The feeding of supplements may have also influenced the estimated RPM data when selecting the six lowest paddocks at each farm walk as a proxy for post-grazing residual. This is due to the amount of supplement being fed being altered depending on individual paddock pasture availability, potentially affecting the overall grazing residual.

During this case study evaluation, the dry matter yield was calculated using the standard RPM equation (CSH × 140 + 500) on both farms. For improved accuracy in future research, measuring post-grazing residuals immediately after each grazing is recommended rather than relying solely on previous farm walk data. This approach would also eliminate the impact of any potential regrowth on the results. For example, the average annual daily growth rate at NARF is approximately 40 kg DM/ha (DairyNZ 2017). However, it should be noted that pasture growth occurs in three distinct phases and in the first phase (recovery phase) directly after grazing, pasture regrowth is relatively minimal until the emergence of the first leaf (Fulkerson and Slack 1994). Additionally, quadrat cuts should be completed to develop linear regression equations to establish the CSH and pasture mass relationship for the pastures being assessed. These paddock and farm-specific equations can enhance the precision of herbage mass estimations made using the RPM. Several factors, such as variability between RPM operators, paddock contour, presence of pugging damage, varying pasture species, seasonal changes, and grazing intensities, can influence the RPM estimates of herbage mass (Lile et al. 2001; Murphy et al. 2021). By accounting for some of these variables, calibration equations thus provide a better basis for evaluating the accuracy of post-grazing residual predictions using animal sensors. Cost constraints prevented the adoption of these approaches in this study.

The grazing management differed between the original study by Edwards et al. (2024), where cows were offered fresh pasture every 24 hours, and the farms in this study, where cows received fresh pasture after each milking, typically every 8 - 12 hours based on milking frequency. This variance in management practices could have impacted the estimates of post-grazing residuals obtained from animal sensors. Specifically, the potential differences in pasture quality and allocation between each feeding event, especially if a new break was introduced in a different paddock, might have influenced subsequent rumination and eating times, which are critical predictors in both the smaXtec and AfiCollar equations used for estimating post-grazing residuals.

Despite the limitations identified, given that the use of animal sensors could predict post-grazing residuals in near real-time and requires minimal effort to collect the data, combining the sensor data with other pasture assessment measures such as visual pasture evaluation or RPM data could assist in on-farm feeding decisions such as changing pasture or supplement per cow allowances, thereby optimising feeding strategies. For example, increasing estimates of residual pasture mass may mean a decrease in pasture utilisation on-farm, potentially affecting future pasture quality and milk production. Early warning of this occurring on-farm could prompt proactive management interventions to optimise pasture utilisation and reduce milk production costs, which could involve adjusting grazing areas or supplement amounts at the herd level. Conversely, decreasing residual pasture mass might lead to management interventions such as introducing supplements or reducing feed demand (e.g., culling or drying off cows) to meet daily cow feed requirements.

Although knowing the post-grazing residual is helpful for pasture management on dairy farms, it is only one part of a successful pasture management approach. Average farm pasture cover and the feed wedge are also valuable metrics. Average farm pasture cover provides a snapshot of total pasture availability, aiding in future grazing and feed allocation planning to ensure consistent feed supply. By contrast, the feed wedge, representing pasture distribution across paddocks, supports rotational grazing decisions and optimal grazing times for pasture health and animal nutrition. Therefore, the results of this study should be viewed as part of a broader pasture management toolkit rather than a standalone solution. Integrating post-grazing residuals with average pasture cover and the feed wedge allows farmers to make more precise and strategic decisions, ultimately enhancing grazing efficiency and pasture productivity.

Conclusion

The utilisation of activity and rumination data from sensors for estimating post-grazing residuals on-farm has been previously demonstrated in experimental settings for multiparous Friesian-Jersey cross dairy cows grazing perennial ryegrass dominant pasture in Canterbury utilising 24 hour grazing breaks on a pasture only diet (Edwards et al. 2024). The current investigation highlights factors that may impede its broader applicability. These factors include supplement feeding, differences in pasture species type, and various management practices, including mulching and frequency of fresh pasture allocations. Despite these challenges, combining sensor data with subjective assessments, such as visual pasture assessment, holds promise for informing decisions related to pasture management and dairy herd feeding. Further research is warranted to refine the predictive models and identify the specific contexts in which this integrated approach can provide tangible benefits to dairy farmers in New Zealand.

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