Challenges in using on-farm animal data for pasture dry matter intake calculations

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Abstract

Accurate estimation of dry matter intake (DMI) is crucial for on-farm feed management and research, including calculating methane emissions. However, direct measurement of DMI (e.g., using n-alkanes, cut-and-carry systems) is labour-intensive and impractical for routine use. Researchers and industry organisations have developed back calculation as an alternative option for estimating DMI based on theoretical energy demand equations. However, this method relies on having accurate and complete data for input variables such as animal liveweight, milk production, and supplements fed, which can be challenging to obtain in practice. Using a research farm case study, we identify common issues encountered when applying this approach. Key issues include approaches for aggregating high-resolution, but noisy and incomplete, animal-level data to the scale required by energy demand equations that are intended for application at the group level over a longer time scale. Use of models (e.g., generalised additive models) for smoothing and interpolating individual animal data before aggregation is shown to be effective. Disaggregation of herd data onto shorter time steps (e.g., hourly) is also highlighted as a possible solution to the challenge of aligning data obtained at variable time steps (e.g., milk yields). Finally, a structured approach is proposed to support researchers who develop or apply energy-based equations to predict DMI from animal data. In future, advances in technology are expected to overcome many of these data collection limitations and should improve the reliability of back-calculated DMI estimates for both research and industry use.

Keywords: energy requirements, liveweight, pasture disappearance, dairy cows, milk production

Introduction

Estimating the dry matter intake (DMI) of grazing animals is a critical component of both farm management and agricultural research. On the farm, DMI underpins feeding strategies and grazing management, ensuring animals get adequate nutrition to achieve farm production targets. In agricultural research, accurate DMI estimates are vital for understanding animal responses such as growth rates, reproductive performance, and milk production. Beyond animal productivity, DMI is crucial in environmental assessments, especially for estimating methane (CH_4) emissions. In New Zealand, agriculture makes up about 50% of the country's total greenhouse gas emissions, with the dairy industry responsible for nearly half of this figure (Ministry for the Environment 2024). Methane is a significant greenhouse gas primarily produced as a normal byproduct of feed fermentation by rumen microbes, and methane emissions are closely linked to total DMI (Patra 2016; Roques et al. 2024). Therefore, improving the accuracy of DMI estimation is not only key to optimising livestock performance but also vital for quantifying emissions and developing effective strategies to reduce methane output from the livestock sector.

In a research context, indoor cut-and-carry systems are the primary method for estimating DMI. While these systems can provide reliable estimates of DMI, they are costly, labour-intensive, and can only be conducted for small numbers of animals, making them unrepresentative of grazing systems. In contrast to total mixed ration (TMR) farming systems (e.g., United States), where feed is delivered directly to the herd, New Zealand's pastoral systems require animals to forage for their feed, introducing unique challenges for monitoring and managing DMI. Several tools and methods have been introduced to estimate DMI, including manual tools that measure herbage disappearance (e.g., rising plate meter), digital pasture measurement tools (e.g., C-Dax pasture meter), internal and external indigestible markers such as n-alkanes, animal sensors that can provide an estimate of DMI using proprietary algorithms (e.g., Ceres Trace), and predictive intake equations based on energy demand assumptions (Smith et al. 2021; Stubbs 2023). None of these methods is widely adopted currently, due to cost, time requirements, or insufficient accuracy (Undi et al. 2008; Smith et al. 2021).

Predictive intake equations based on energy demand assumptions provide an alternative to indoor cut-and-carry trials for estimating DMI in cows grazing on pasture and can be used to calculate the DMI of individual animals on a large scale (Halachmi et al. 2004). Several systems of predictive equations have been developed, including the National Research

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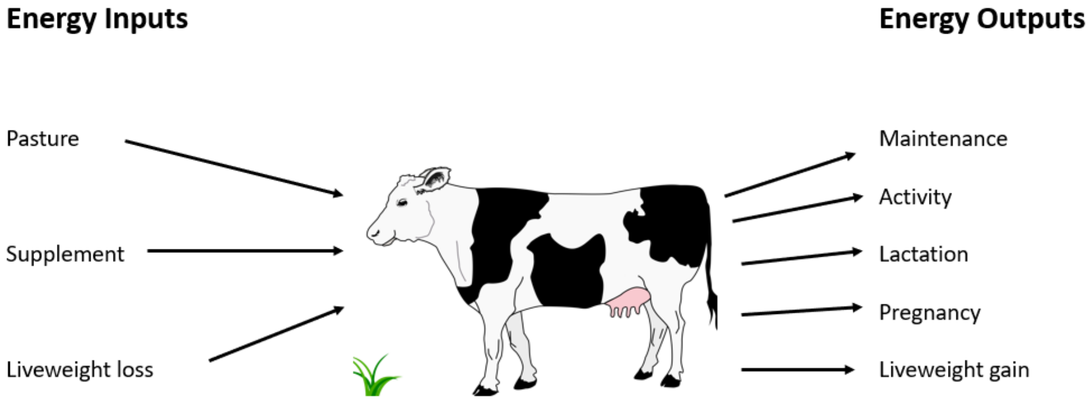

Figure 1 Dairy cow energy inputs (e.g., feed) and energy outputs (e.g., milk).

Council (NRC) 2001 equations (National Research Council 2001), Ministry for Primary Industries Greenhouse Gas (MPI GHG) inventory equations (Pickering et al. 2024), and Nicol and Brooke's equations (Nicol & Brookes 2007). These equations estimate animal DMI indirectly by accounting for the energy required for key metabolic functions, such as maintenance, production (e.g., milk production for dairy cows), liveweight change, pregnancy, and activity (Nicol & Brookes 2007; Stubbs 2023). Energy inputs come from pasture, supplements, and any liveweight loss, while energy outputs are used for maintenance, activity, lactation, pregnancy, and liveweight gain (Figure 1). The balance between these inputs and outputs determines whether the animal gains or loses weight. Pasture intake is then inferred by subtracting the energy provided from supplements, if applicable, from the animal's total energy requirement and dividing the remainder by the pasture's metabolisable energy (MJME) content, e.g., Haultain (2014).

The reliability of DMI predictions made using this approach depends on the availability and quality of input data, such as animal liveweight, milk production, imported supplements and feed quality data for both supplement and pasture, which may not always be readily accessible or accurate (Brookes & Holmes 1988; Halachmi et al. 2004). Even in a research farm setting with established protocols for routine data collection and storage, erroneous or missing data may make application of these methods challenging. In this paper, we evaluate the suitability of on-farm animal data for use in energy intake calculations for lactating cows on a commercial-scale research farm, focusing on data handling, processing, and quality considerations when applying predictive intake equations to farm-collected data. We highlight the challenges related to data availability and accuracy and outline the minimum and preferred requirements for implementing the energy back calculation process in commercial or research farm settings.

Data collection and analysis

Energy equations

Energy equation models typically require a range of animal-specific information, such as breed, age, production level, and pregnancy status, to estimate energy requirements at both the individual cow and herd levels and form the foundation for estimating DMI when direct measurements are unavailable. In this study, the predictive equations of Nicol and Brookes (2007) were used to define the energy balance of dry and lactating dairy cows. Compared to other energy equation models, such as the MPI GHG energy equations, the Nicol and Brookes (2007) energy equations are better suited for calculating individual animal DMI, the primary objective of the current study, because they incorporate animal-specific parameters such as breed, age, production, and pregnancy status. In contrast, equations such as the MPI GHG equations are designed for national-scale emissions reporting and instead use population averages to estimate the total metabolisable energy and dry matter requirements (Pickering et al. 2024). Therefore, for research focused on individual-level intake estimation, the Nicol and Brookes (2007) equations are more appropriate.

Scale of aggregation

To apply such equations, a suitable scale must be chosen. Energy equations, such as those proposed by Nicol and Brookes (2007), are developed using a large corpus of data across multiple studies and the number of animals observed at various time scales while subject to controlled experimental conditions (Zhang et al. 2021). As a result, the equations are most suitable for application at the aggregate level (i.e., a group of cows, on a daily basis) rather than for individual cows at high resolution. When applying them to farm data, a suitable reference scale must be chosen that allows individual and herd-level animal data collected on a per-milking, per-day, or multiple-day basis to be combined.

Given that the objective of the current work is inferring pasture intake, the relevant scale is per herd per paddock. However, herd information (e.g., daily milk production and energy requirements) is often calculated from individual animal data (e.g., milk meters, walk-over scales), making individual animal tracking particularly useful for identifying outliers and trends. In this study, energy requirements were calculated for individual animals on an hourly time step, in anticipation of aggregation to the per-herd-per-paddock scale for back calculation of DMI. The accuracy of the calculations for individual animals is unlikely to be high (Bown et al. 2013).

Farm data

The case study used data from a DairyNZ-led farm systems study conducted at the Southern Dairy Hub (SDH) during the 2023/24 dairy season (June 1 – May 31). SDH is a 349-hectare research dairy farm with flat topography situated on two terraces in Wallacetown near Invercargill, New Zealand. Farm data included daily individual cow milk production from inline milk meters (DeLaval Delpro) as well as herd bulk milk collection data (Fonterra bulk milk vat data). The DelPro data provided cow-level milk volumes, while the Fonterra data provided both bulk milk volumes and fat and protein percentages at each milk pickup. These complementary data sources were used to assess consistency between data sets and to support energy intake calculations based on milk composition. Additional data included LIC MINDA herd test results (milk composition for up to 12 separate tests per year per cow), daily liveweights and body condition scores (BCS) whilst lactating (DeLaval in-shed walk-over scales and DeLaval BCS camera), and manually recorded herd grazing records to help estimate daily activity levels (e.g., distance walked).

Data preprocessing

Before analysis, the data were preprocessed to ensure unit consistency, handle missing values, and manage outliers. Where raw data were noisy or missing, smoothing techniques (to remove noise and fluctuations in the data) and interpolation techniques (to estimate unknown values) were used to estimate the animal variables at the required time steps. Smoothed and interpolated variables included daily milk yield per milking, fat and protein percentages, liveweight, and body condition score change. The models used for smoothing were either linear regression models (LM) or Generalised Additive Models (GAM), which are flexible regression models that extend Generalised Linear Models (GLM) by incorporating smooth functions to describe nonlinear relationships between the predictor and response variables (Hastie & Tibshirani 1990). All analyses were performed using R Statistical Software (v4.2.1; R Core Team 2022) and RStudio (v2024.4.0.735; Posit Team 2024). The models were developed using the "gam" function from the mgcv library in R (Wood 2017) with the restricted maximum likelihood (REML) option to minimise overfitting.

Following preprocessing, data completeness was assessed. Liveweights were recorded at each milking event as cows exited the farm dairy. Based on milking frequency, either twice daily (TAD) or once daily (OAD), a total of 335287 liveweight records were expected. However, only 230559 records were captured, corresponding to a 68.8% completeness rate. Of these, 32673 records (14.2%) were excluded due to errors with the load bar sensors, further reducing the usable dataset. For milk yield, the same number of records as per the liveweight data were expected, with 329,595 recorded (98.3% completeness) and 5,692 records (1.7%) missing. Body condition scores (BCS) were recorded once daily per cow, resulting in 190770 expected records, of which 189584 (99.4%) were successfully captured. These findings highlight the variability in data completeness across traits and emphasise the importance of robust data quality checks during analysis.

Below are details regarding the specific implementation of the GAM process for each data type (i.e., milk volume, fat and protein percentages, liveweight, and BCS change).

Milk volume

Milk production (litres) was smoothed using a GAM function based on the day of the season (days since 1 June), as well as milking frequency (once a day or twice a day) and milking time (morning or afternoon) as fixed effects.

The observed milk production values for individual cows were used as input data for the GAM model. Residuals were calculated as the difference between actual and predicted milk values. Outliers in the residuals were identified using Tukey's method (Newman 2023) and flagged as values outside the lower and upper bounds. Missing data were also addressed, particularly for specific milking times or frequencies. Outliers and missing values were replaced with the predicted milk values to ensure a more consistent dataset for further analysis.

Figure 2 illustrates the interpolation and smoothing

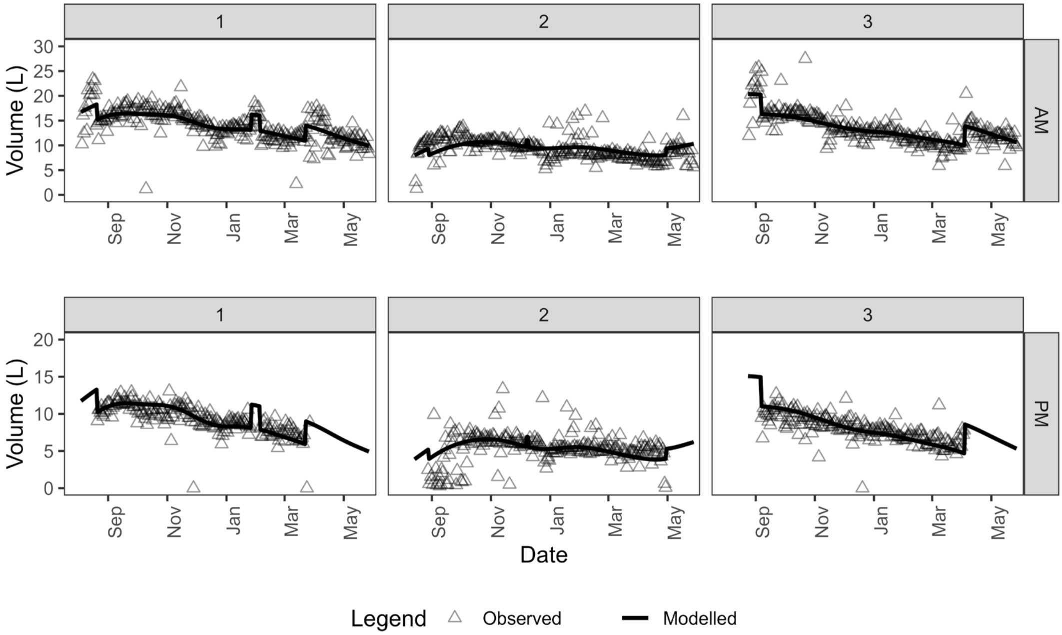

Figure 2 Observed milk volume from DeLaval Delpro data (converted from kg to litres) and smoothed milk volume for each milking. Each facet represents an individual cow chosen randomly, with the top row corresponding to morning (AM) milking and the bottom row to evening (PM) milking. Discontinuities in the smoothed milk volume curve reflect transitions between once-a-day and twice-a-day milking.

of the daily milk volume for a subset of the herd. As expected, milk production declined over time due to the progression of the lactation stage, with the predictions closely aligning with the observed data. However, some deviations occurred, possibly due to variations in feed quantity and quality, faulty milk meters, missed milkings, or missing Radio Frequency Identification Devices (RFID eartags). These were replaced using the smoothing model.

Milk fat and protein percentages

A linear regression model was used to predict individual cow fat and protein percentages using the MINDA herd test data. The predictor variables included cow identification number, milking time (morning or afternoon), bulk milk composition (derived from bulk milk vat data), and the day of the season. A quadratic term for the day of the season was incorporated to account for potential non-linear trends. This model was then applied to the extended dataset to estimate fat and protein percentages for individual cows where actual values were unavailable.

Figure 3 shows the observed fat and protein percentages from the MINDA herd test results alongside the modelled fat and protein percentages for a subset of cows, highlighting a clear seasonal trend. Both fat and protein percentages increased over time, as expected. The devised model closely aligned with the observed data, capturing seasonal fluctuations, although some deviations in predictions are evident, such as the fat percentage. These results demonstrate the models' ability to follow milk composition trends.

Liveweight and body condition score

Like milk production, the cow liveweight and BCS data were smoothed using GAM models, with smooth terms for the day of the season and fixed effects for the cow identification number. The liveweight model used individual cow liveweights obtained from daily walk-over weighing, while the BCS model incorporated daily BCS measurements captured by a DeLaval BCS camera. This camera captures 3D images of each cow as it passes under the camera, sending the information back to the DeLaval Delpro system (DeLaval 2025).

Figure 4 illustrates the performance of the models for animal liveweight and BCS. The liveweight data were unstable and subject to sensor drift. Cow misbehaviour, such as rapid or erratic movement, multiple cows on the scale simultaneously, or forceful stepping, can also cause inaccurate liveweight readings (Dickinson et al., 2013). The modelled trend follows the general pattern of the observed data, capturing the gradual increase over time and helping smooth out the effect of changes in gut fill. The BCS model similarly followed the general trend of the observed BCS data. The model accurately captured the decline in BCS from July to

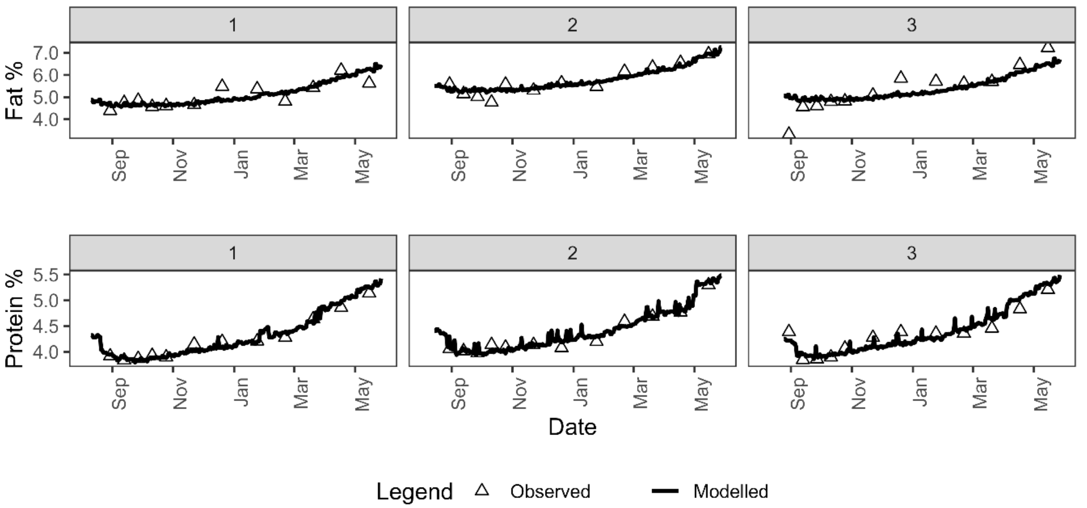

Figure 3 Observed fat and protein percentages from MINDA herd test data and modelled fat and protein percentages, with each facet representing an individual cow.

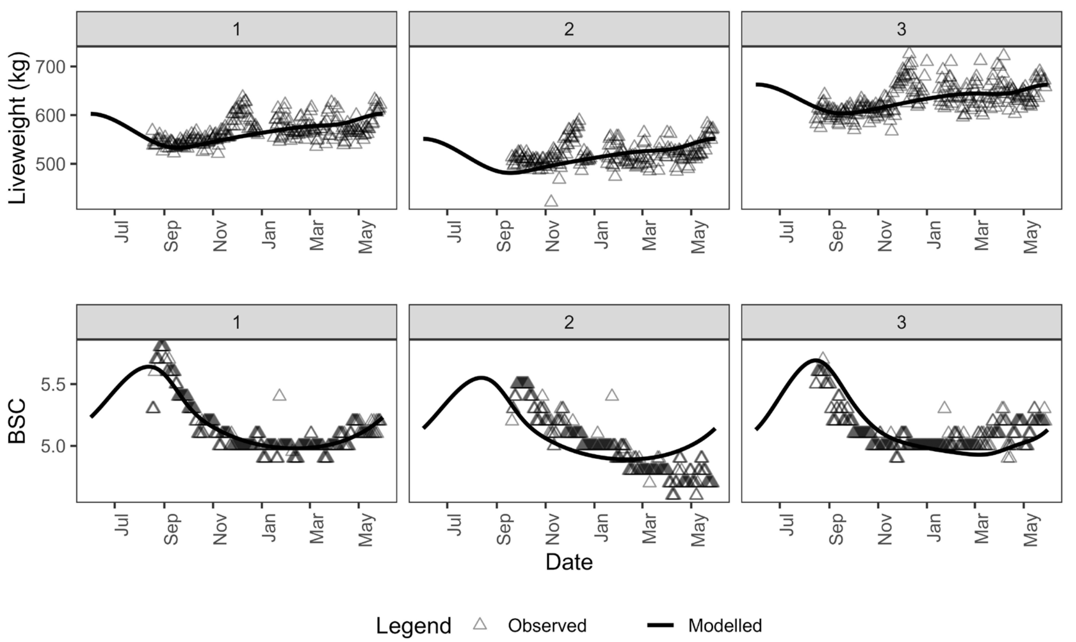

Figure 4 Observed liveweight (from walk-over weighing) and body condition scores (BCS, from in-shed camera) and modelled values.

January, consistent with body fat mobilisation during early lactation, before stabilising and increasing later in the season as lactation demand decreases, leading to a replenishment of body reserves.

Activity

In addition to the energy required for maintenance, which is the amount of energy required to keep an animal at a constant body weight, energy is also required for activities such as walking during grazing and travelling to and from the milking shed. The energy cost of activity varies based on the distance walked and the topography (Nicol & Brookes 2007). In this study, a fixed activity allowance was made using the values proposed by Nicol and Brookes (2007). In future, improved estimates of daily distance travelled per cow could be obtained using wearable technologies with GPS functionality, such as eShepherd and Halter, as demonstrated by Hendriks et al. (2025).

Discussion

Data processing challenges

This study highlights specific challenges in using predictive intake equations to backcalculate DMI on commercial farms. Energy equations such as those by Nicol and Brookes (2007) require clean and complete input data at a suitable scale and are intolerant of errors. Errors in farm data, however, are common, due to the complexities of dairy grazing systems and the difficulty of obtaining consistent and complete measurements of many key animal-level variables. This was evident in our study, where liveweight data were only 68.8% complete and further reduced by 14.2% due to sensor errors. Milk yield and BCS also showed varying degrees of incompleteness. Furthermore, back calculation of DMI intake requires combining multiple types of farm data at different scales of animal (individual, herd) and time (per milking, per break, weekly, monthly) aggregation onto a standardised scale (e.g., per cow per hour). Data may be missing or misrepresentative due to faulty equipment (e.g., weigh scales, in-line milk meters), misidentification of cows (e.g., on rotary platforms), or human recording errors during manual data entry. As a result, miscoded and missing data require extensive correction, smoothing, and interpolation to produce a consistent dataset that allows the matching of cow energy inputs and outputs. Smoothing techniques, such as GAM models, are helpful for smoothing and interpolating high-resolution but noisy data with gaps.

To support practical application, Table 1 presents the suggested, proposed minimum, and preferred data requirements for back-calculating animal feed intake based on energy requirements and supplements fed. These serve as a guide for assessing whether available farm data are fit for this purpose.

Commercial application

While the SDH farm operates at a commercial scale, it also serves as a research farm and so has detailed data collection protocols (such as daily milk records per cow, daily liveweights and BCS for individual animals and daily livestock counts) that surpass what is typically available on commercial farms. This highlights a key challenge for applying similar methods to commercial farms, where access to detailed, timely data may be even more limited. For commercial farms, the lack of consistent data collection, particularly regarding daily livestock counts, paddock grazing records, and supplement feeding, means that applying this methodology could lead to less reliable estimates, requiring additional assumptions that could reduce the accuracy and confidence of the results.

Tools such as FARMAX, which integrate farm system data to model feed supply, animal demand, and estimate pasture intake, are available to help estimate DMI. However, while useful, these models, which often operate at the herd or system level, rely on assumptions such as pasture and supplement quality rather than high-frequency, individual-level records (FARMAX 2025). Therefore, while models like FARMAX can provide valuable insights, especially where detailed data is lacking, there remains an opportunity to improve precision through enhanced on-farm data capture.

Improving data quality and consistency on commercial farms would not only enhance DMI estimates but also support improved methane emissions model estimates. Without robust data collection on commercial farms, methane estimates are subject to greater uncertainty, which may limit the effectiveness of emissions reduction strategies.

Technology integration

Integrating technology could be a valuable tool to help overcome some of the limitations in data collection on commercial farms and enhance the reliability of DMI estimates derived from predictive energy equations. For example, today, several commercially available devices have the potential to provide real-time data on key variables, such as livestock movements and the volume of milk produced per milking. These technologies may help bridge the data gaps currently faced by commercial farms and enable more accurate estimates of DMI using the back calculation methodology.

Technology can be particularly beneficial in recording grazing data, as many farmers often fail to capture this information consistently. For example, an increasing number of farmers are utilising virtual fencing technology, such as Halter (Halter 2025), which allows grazing data to be automatically captured. Alternatively, farmers could fit a proportion of each herd with devices with GPS functionality, such as Ceres Trace or GSat Solar, which would also allow automatic capture of the grazing data (Hofmann 2022; Hofmann et al. 2024).

Animal wearables could also be valuable for recording the number of animals in each herd daily, as on larger farms, cows may frequently move between herds (e.g., from the milking herd to a treatment herd or a twice-a-day herd to a once-a-day herd). Virtual fencing technology could also play a role in this; alternatively, several products on the market can count the number of cows entering or exiting the cowshed during milking. This solution is beneficial for farms with rotary sheds. However, this approach relies on cows being fitted with RFID ear tags. If any cows are missing their ear tags, they will not be included in the count, which can reduce

Table 1 Preferred and minimum data requirements for back-calculating animal dry matter intake based on energy requirements and supplements fed.

Item	Preferred requirement	Source	Minimum requirements	Source
Grazing records	Daily records of when and where the dairy herd has grazed.	Automated with virtual fence system devices (e.g., Halter) or other wearables containing GPS functionality, e.g., Ceres Trace	Daily records of where the dairy herd has grazed.	Manually recorded by the farmer or research technician.
Milk records	Daily individual records of milk production per cow per milking	Through individual inline milk meters at each milking	Daily milk production records are provided for each milking	Vat monitoring technology, e.g., Halo or Levno.
Cow numbers	Daily number of cows in each herd on-farm, and which animals are in which herd.	Automated with virtual fence system devices (e.g., Halter) or other technology at the cowshed, e.g., auto drafters	The weekly number of cows in each herd on-farm is recorded	Manually recorded by the farmer or research technician
Pasture and supplement quality	Pasture and supplement quality samples, including MJME, are taken regularly, e.g., monthly.	Scientific laboratory, e.g., Hills or ARL	Without regular samples, assumptions for ME in the diet must be made based on a best estimate for the diet components (pasture and supplements).	Published source, e.g. DairyNZ Facts & Figures https://www.dairynz.co.nz/resources/resource-list/facts-and-figures/
Cow liveweight	Daily liveweights are taken for each cow as they enter/leave the milking shed.	Walk-over weigh systems	Liveweights are estimated based on breed proportions, with changes in liveweight calculated using relevant regional data.	Liveweight breeding values (BV) adjusted for farm systems differences. Liveweight change is extrapolated from other farms or research data.
Body condition score (BCS)	Change in BCS is estimated for each animal for each week of the year.	This can be done automatically via an in-shed BCS camera or through regular assessments by trained assessors.	Not required	Assumes that BCS data is captured in the liveweight data estimated above.
Daily distance walked	The distance from each paddock to the shed is known.	GPS farm maps or calculated from animal wearables with GPS or pedometer functionality.	If distances are unknown, they are estimated based on the number of kilometres walked per day.	Estimated using suitable measuring equipment, e.g., vehicle odometer
Pregnancy data	Individual calving dates are known for each animal	Herd record provider, e.g. LIC or CRV or pregnancy scanner, e.g., vet	Group calving dates are known.	Farmer
Pasture records (if wanting to compare back-calculated DMI to pasture disappearance)	Pre- and post-grazing measurements are used to estimate pasture harvest and compare them with back-calculated predictions.	Automated pasture measurement technology, such as satellite-based pasture measurement systems (e.g., Pasture.io, is utilised.	Pasture is manually measured using a rising plate meter, C-Dax tow behind, etc.	Manually recorded by the farmer or research technician.
Supplement or crops fed.	Daily records of supplements fed to each herd.	Automated using suitable technology, such as tractor weigh scales and recording technology.	Daily records of supplements fed to each herd.	Manually recorded by the farmer or research technician.

the accuracy of the provided cow counts. Additionally, depending on the milking system in rotary sheds, empty bales or unexpected cow movements can cause misalignment between the order of cows and the data collected (e.g., milk yield), resulting in incorrect cow-level data. Under these circumstances, farms may need to rely on herd-level estimates of intake, limiting the precision and value of individual animal data collection

On many farms, multiple herds are often milked into a single vat, making it challenging to distinguish the individual milk volumes produced by each herd. Fortunately, many dairy processors have installed vat monitoring technologies, such as Levno (Levno 2023) and Halo (Halo Systems 2024), on farms to enhance their efficiency, for example, by scheduling milk pickups more effectively. These technologies, which estimate the milk volume in the vat, among other features, could also improve daily milk volume estimates for each herd, especially in cases where inline milk meters are not installed.

Pasture data considerations

While this paper focuses on animal-level data, pasture data collection presents a different set of challenges due to its spatial and temporal variability. For example, pre- and post-grazing residuals are typically collected less frequently and at the paddock level, limiting their alignment with the daily intake estimate. Paddocks may also be subdivided for grazing (e.g., strip grazing, back fencing) or cutting, and this subdivision is often not recorded. Although data from regular farm walks can be helpful, these assessments may not fully capture within-paddock variability or sudden changes due to weather or grazing behaviour. Likewise, not all farmers conduct farm walks for various reasons, including the time-consuming nature of pasture measurement, limited confidence in the value proposition of measurement tools and concerns regarding their accuracy (Anderson & McNaughton 2018; Leddin et al. 2023). Improving DMI estimates through better animal data may, in future work, support more accurate back calculation of pasture harvested.

Conclusions

Accurate estimation of dry matter intake (DMI) on commercial dairy farms remains challenging due to incomplete or inaccurate records of key variables such as liveweight, milk yield, and pasture quality. While energy-based equations offer a practical method to estimate DMI, their reliability heavily relies on precise input data. In commercial settings, missing or estimated values often necessitate assumptions that reduce confidence in the results. Emerging technologies, including animal sensors and vat monitoring systems, offer the potential to improve DMI estimates by delivering more frequent and objective data. However, their integration into farm systems is still limited, and some inputs, such as supplementary feed intake, will continue to need manual recording. Future research should focus on practical methods to combine automated and manual data sources to enable more reliable DMI estimation at both the herd and individual animal level.

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