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Usefulness of mid-infrared spectroscopy as a tool to estimate body condition score change from milk samples in intensively-fed dairy cows

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ABSTRACT

Directly measuring individual cow energy balance is not trivial. Other traits, like body condition score (BCS) and BCS change (Δ BCS) can, however, be used as an indicator of cow energy status. Body condition score is a metric used world-wide to estimate cow body reserves and the estimation of Δ BCS was, until now, conditional on the availability of multiple BCS assessments. The aim of the present study was to estimate Δ BCS from milk mid-infrared (MIR) spectra and days in milk (DIM) in intensively-fed dairy cows using statistical prediction methods. Daily BCS was interpolated from cubic splines fitted through the BCS records and daily Δ BCS was calculated from these splines. Body condition score change records were merged with milk MIR spectra recorded on the same week. The data set comprised 37,077 Δ BCS phenotypes across 9,403 lactations from 6,988 cows in 151 herds based in Quebec (Canada). Partial least squares regression (PLSR) and a neural network (NN) were then used to estimate Δ BCS from 1) MIR spectra only, 2) DIM only, or 3) MIR spectra and DIM together. Δ BCS data in both the first 120 DIM and 305 DIM of lactation were used to develop the estimates. Daily Δ BCS had a standard deviation of 4.40×10^{-3} BCS units in the 120-d data set and of 3.63×10^{-3} BCS units in the 305-d data set. 4-fold cross-validation was used to calibrate and test the prediction equations. External validation was also conducted using more recent years of data. Irrespective of whether based on the first 120 or 305 DIM, or when MIR spectra only, DIM only or MIR spectra and DIM were jointly used as prediction variables, NN produced the lowest root mean square error (RMSE) of cross-validation (1.81×10^{-3} BCS units and 1.51×10^{-3} BCS units, respectively, using the 120-d and 305-d data set). Relative to predictions for the entire 305 DIM, the

RMSE of cross-validation was 15.4% and 1.5% lower in the first 120 DIM when using PLSR and NN, respectively. Predictions from DIM only were more accurate than those using just MIR spectra data but, irrespective of the data set and of the prediction model used, the combining DIM information with MIR spectral data as prediction variables reduced the RMSE compared with inclusion of DIM alone, albeit the benefit was small (the RMSE from cross-validation was reduced up to 5.5% when DIM and spectral data were jointly used as model features instead of DIM only). However, when predicting extreme Δ BCS records, the MIR spectral data was more informative than DIM. Model performance when predicting Δ BCS records in future years was similar to that from cross-validation demonstrating the ability of MIR spectra of milk and DIM combined to estimate Δ BCS, particularly in early lactation. This can be used to routinely generate estimates of Δ BCS to aid in day-to-day individual cow management.

Keywords: prediction, energy balance, neural networks, body condition score

INTRODUCTION

Early lactation dairy cows experience negative energy balance, although the extent and duration varies per animal (de Vries and Veerkamp, 2000; Oikonomou et al., 2008; Olson et al., 2010). This phenomenon in dairy cows is exacerbated as the result of breeding programs in the late 20th century, most of which focused on milk yield alone, resulting in feed intake capacity being insufficient to deliver the greater energy requirement for the increased milk production (Van Arendonk et al., 1991; Veerkamp et al., 2001). The subsequent observed erosion in reproductive performance of most dairy cow populations (Bagnato and Oltenacu, 1994; Lucy, 2007; Berry et al., 2014) contributed to a broadening of dairy cow breeding goals shifting the emphasis from productivity only to a combination of production and functionality traits (Miglior et al., 2005; Miglior et al., 2017;

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Cole and VanRaden, 2018). Indirectly, such a strategy attempts to improve the energy balance of dairy cows (Banos and Coffey, 2010); nonetheless, growing interest in feed efficiency in dairy cows could, if not properly undertaken, have repercussions for energy balance given the close mathematical relationships between some definitions of feed efficiency and energy balance (Hurley et al., 2018). Energy balance is, however, a difficult trait to accurately measure directly. Other traits, like body condition score (BCS) and BCS change (Δ BCS) are indicators of cow energy status; cows in negative energy balance will attempt to fulfill the energy deficit by mobilizing body (fat) reserves which are reflected in a change in BCS. Body condition score is easy to assess and is known to be related to fertility and health traits (Roche et al., 2007; Roche and Berry, 2006; Pryce et al., 2001). Hence, being able to monitor Δ BCS in dairy cows, especially in early lactation, can be useful to identify at-risk cows early and, in doing so, enable early interventions. Nevertheless, access to temporal measures of individual cow Δ BCS is conditional, until now, on routine BCS assessment by producers which can be time consuming. This is because multiple BCS records are needed to calculate Δ BCS. Cows should ideally be restrained for body condition scoring, thus slowing down entry or exit to a milking parlor but also demanding a resource at a time when resources are already stretched (i.e., milking). Whereas digital-based solutions exist to condition score animals (Azzaro et al., 2011; Mullins et al., 2019), these technologies incur an initial capital cost as well as routine maintenance costs; furthermore, their accuracy is not perfect (Mullins et al., 2019; Spoliansky et al., 2016). An alternative was originally proposed by McParland et al. (2014), who estimated Δ BCS in Irish dairy cows using only mid-infrared (MIR) spectral information of milk samples; this approach was advanced by Frizzarin et al. (2023) who documented an improvement up to 7% in prediction accuracy of Δ BCS in early lactation by also considering days in milk (DIM) as a prediction variable coupled with using neural network as opposed to the traditional partial least squares regression used by McParland et al. (2014). In fact, Frizzarin et al. (2023) reported a correlation between the real and the estimated Δ BCS of 0.86 following 4-fold cross-validation; this study was based on seasonal-calving dairy cows on a predominantly grazed pasture diet and only originated from a small number of research farms.

The main aim of the present study was to quantify the ability of routinely available MIR spectral data from milk samples of intensively-fed Canadian dairy cows, with or without consideration of DIM, to estimate their Δ BCS with a particular focus on Δ BCS in early lactation. The approach used was similar to that

described by Frizzarin et al. (2023) when investigating its potential in grazing dairy cows, but here the approach was applied to Canadian cows which differ in feeding, genetic merit, housing, and management.

MATERIALS AND METHODS

Data

Lactanet Canada (Guelph, ON) provided a total of 347,254 BCS records from 80,400 cows collected from 1,110 commercial farms based in Quebec (Canada) between the years 2017 and 2022, inclusive. Body condition score was assessed on a scale from 1 (emaciated) to 5 (obese) in increments of 0.25 units (Edmonson et al., 1989) by either trained scorers or producers. The number of BCS records per cow-parity ranged from 1 to 25. The cows scored represented a range of parities (i.e., 1 to 12) and breeds (i.e., Holstein, Jersey, Brown Swiss, Ayrshire, and Guernsey). The majority of the farms were tie-stall feeding a TMR.

A total of 1,258,766 individual milk spectra were also provided by Lactanet for these herds across all years. Milk samples for spectra analyses were collected during routine milk recording. All milk samples were analyzed using MIR spectrometers located at the Lactanet Lab in St Anne de Bellevue, Quebec (Foss MilkoScan FT+; Foss Electric A/S, Hillerød, Denmark) generating 1,060 spectral values per sample.

Data Editing

The high-noise-level regions of each spectrum were removed leaving 531 wavelengths for analysis. The Mahalanobis distance of each edited spectrum from the centroid was calculated using the first 7 principal components which explained 99% of the spectral variability. Outlying spectra were deemed to be those with a Mahalanobis distance from the centroid greater than the 99th quantile of all the computed distances, and were removed (Frizzarin et al., 2021).

Body condition score data from 11,699 cow lactations were available after removing cows that resided on more than one farm during the lactation; data from cow lactations with less than 5 BCS records and farms with less than 5 animals recorded across the available years were also discarded. Furthermore, only BCS data recorded in the first 305 DIM were retained.

To generate Δ BCS phenotypes, cubic splines with 6 knot points at 20, 50, 80, 170, 220, and 270 d in milk (DIM) were fitted through individual test-day records of BCS per lactation separately with a covariance structure fitted among knot points as per McParland et al. (2014). From the fitted splines, daily BCS was

interpolated. From these, Δ BCS was calculated as the BCS on a given day minus the BCS of the previous day. Only calculated Δ BCS records coinciding with a day when an actual BCS record was available were retained. Body condition score change records were merged with the respective animal's milk spectral data by calendar week.

To avoid any potential bias in the validation procedure of the MIR estimates of Δ BCS, 4-fold cross-validation was undertaken where the data set was divided into 4 sub-data sets with all repeated observations from the same cow lactation assigned to the same sub-data set. The spline fitting was again undertaken in total 4 times, each time including a new combination of 3 of the 4 subsets. Hence, Δ BCS phenotypes were available for all animals using all available data but also Δ BCS phenotypes were available where a subset of the data was not included; the former data set was used for validation of the developed MIR equations with the latter used in the development of the MIR equations.

Parities were grouped as first, second, and third or greater. Stage of lactation was collapsed into early (i.e., between 5 and 120 DIM), mid (i.e., between 121 and 200 DIM), or late (i.e., between 201 and 305 DIM) lactation. Outliers for Δ BCS were identified as those > 3 standard deviations from the mean for the respective stage of lactation within each parity group and these outliers were discarded. The final data set comprised 37,077 Δ BCS phenotypes across 9,403 lactations from 6,988 cows in 151 herds. A sub-data set was generated using only Δ BCS phenotypes in the first 120 DIM and comprised 15,874 Δ BCS phenotypes across 8,018 lactations from 6,045 cows.

Using the 4 subsets of data previously generated, MIR equations to estimate Δ BCS were developed using the Δ BCS phenotypes in 3 of these subsets and validated against the Δ BCS phenotypes in the fourth subset (i.e., 4-fold cross-validation). This was iterated 4 times in total so that all the sub-data sets were used once for testing. To explore the ability of the models to estimate Δ BCS in cows losing BCS at the fastest rate (i.e., cows arguably of most interest), the predictive ability of the most extreme 2.5% records losing BCS at the fastest rate per DIM was separately investigated. Moreover, to further test the ability of the prediction methods to estimate future data (i.e., a form of external validation), a prediction equation was developed using the data collected between 2017 and 2020 (i.e., the calibration data set), and then validated using the data collected in 2021 and 2022 (i.e., the validation data set). Cows present in the training data set were not present in the validation data set.

Development of the Equations

Two different methods were evaluated for their ability to estimate Δ BCS: partial least squares regression (PLSR) and a neural network (NN). Three approaches to developing the prediction methods for Δ BCS were evaluated; 1) using only MIR spectral data, 2) using only DIM, and 3) using both MIR spectral data and DIM together. Days in milk was included in all models as a continuous trait and, for PLSR predictions, a fourth order polynomial of DIM was considered. All the analyses were conducted using the statistical software R 3.6.1 (R core team, 2021). In the 4-fold cross-validation, the calibration data set was 3 of the 4 sub-sets with the fourth subset representing the validation data set; this was iterated 4 times with a different subset each time. The analyses were undertaken separately using the whole 305-d data set or just the 120-d data set.

For the development of the PLSR equation, the R package *pls* (Mevik et al., 2019) was used. To identify the best number of latent factors, 10-fold cross validation (CV) was used. The NN equation was developed using the R package *brnn* (Perez Rodriguez and Gianola, 2020) and default tuning parameters were used. These parameters correspond to 2 hidden layers and a Bayesian regularization applied to the input layer.

Measures of Prediction Performance

The metrics used to assess model accuracy were calculated using the estimated values for each test data set and then averaged across the test sets to get overall accuracy metrics. The standard deviation for all these individual performance metrics across test data sets was also calculated and was considered as a reflection of the robustness of the prediction methods. The metrics considered were the bias, the root mean square error (**RMSE**) of prediction, the correlation between the actual Δ BCS values and those estimated from the MIR spectra, the slope, and the ratio of performance to deviation (RPD). The bias corresponds to the average of the residuals while the RMSE is the standard deviation of the residuals. The slope corresponds to the regression coefficient from a simple linear model that regresses actual Δ BCS values (y-axis) on estimated Δ BCS values (x-axis). The RPD is the ratio between the standard deviation of a variable and the standard error of the estimated values of that variable by a given model. To test differences in the mean and in the variance of the residuals between prediction methods, a paired *t*-test and the F-test were respectively used.

RESULTS

Records from cows in first, second, and third or greater parity represented 31.96%, 25.88%, and 42.16% of the total records, respectively. The mean and standard deviation of Δ BCS in the entire 305 DIM data set was -0.14×10^{-3} BCS units and 3.63×10^{-3} BCS units, respectively. The mean and standard deviation of Δ BCS in the entire 120 DIM data set was -2.42×10^{-3} BCS units and 4.40×10^{-3} BCS units, respectively.

Prediction Performance

Prediction performance for PLSR and NN using cross-validation in the 305 DIM and the 120 DIM data sets are summarized in Table 1. Irrespective of the data set considered, or the variables used in the estimation process (i.e., 305 or 120 DIM data set; spectra only, DIM only or DIM and spectral data together), NN produced the lowest RMSE ($P < 0.05$). The number of PLSR factors chosen was always 20 (maximum number allowed) for all 4 cross-validation iterations when DIM and spectral data were together used as prediction variables. With the exception of PLSR using data up to 305 DIM, predictions from models that included both spectral data and DIM produced a lower RMSE ($P < 0.05$) compared with models that considered either just spectral data or just DIM on its own. Nonetheless, relatively good predictive ability was achieved when just the milk spectra or just the DIM was used in predicting Δ BCS with the benefit of combining both sources of information providing a greater advantage compared with when the model was originally based on just the MIR spectra (Table 1). The RPD, which represents the RMSE of validation relative to the SD of the actual phenotype in the data set, was 23.7% and 9.5% better for NN compared with PLSR in the 305 DIM and 120 DIM data sets when DIM and spectral data were jointly used as prediction variables, respectively. The RMSE of Δ BCS predictions in the first 120 DIM was 1.5% (NN) to 15.4% (PLSR) better when predicted using data from just the first 120 DIM relative to when all 305 DIM were considered in the model calibration. When NN was developed using both spectral data and DIM, the correlation between the real and the predicted Δ BCS values was equal to 0.91 both using the 305-d and the 120-d data set. Irrespective of the scenario investigated (i.e., statistical method, variables included into the prediction model, test fold used in the analyses, first 120 or 305 DIM), the bias was never different from zero. Moreover, the slope of actual Δ BCS on predicted Δ BCS never differed from one (Table 1; Figure 1).

The prediction performance from external validation when the equations were calibrated using data collected between the years 2017 and 2020 and validated using data collected in the year 2021 and 2022 are in Table 2; NN achieved the lowest RMSE ($P < 0.05$) both in the 305 DIM data set or the 120 DIM data set. Prediction performance was worst when just the MIR spectra was considered as predictors with the prediction performance based on just DIM being better; however, combining both sources of information achieved a higher prediction performance especially relative to predictions based on just the MIR (Table 2).

When limited to the 2.5% records losing BCS at the fastest rate, the RMSE in the 305 DIM data set was equal to 3.96×10^{-3} BCS units both for PLSR and NN when DIM only was used as a prediction variable; the RMSE reduced to 3.80×10^{-3} and 3.66×10^{-3} BCS units for PLSR and NN, respectively, when just spectral data were used, and to 3.69×10^{-3} and 3.74×10^{-3} BCS units for PLSR and NN, respectively, when spectral data were considered along with DIM in the prediction process. When the 120 DIM data set was used, the RMSE was equal to 5.27×10^{-3} and 5.26×10^{-3} BCS units for PLSR and NN, respectively, when DIM only was used as prediction variable; the RMSE reduced to 4.78×10^{-3} and 4.77×10^{-3} BCS units for PLSR and NN, respectively, when spectral data only were used, increasing to 5.01×10^{-3} and 4.93×10^{-3} BCS units for PLSR and NN, respectively, when the spectral data were jointly considered with DIM in the prediction model.

The average actual Δ BCS across weeks of lactation, as well as the average estimated Δ BCS across weeks of lactation in the first 305 and 120 DIM when DIM and spectral data were jointly used as prediction variables are presented in Figure 2 and Figure 3, respectively. Using the data up to 305 DIM, PLSR prediction of the Δ BCS trend did not reflect well the actual Δ BCS trend up to the 27th week of lactation. In contrast, the trend in predicted Δ BCS from NN followed the actual Δ BCS trend well.

DISCUSSION

Consistent with results from international studies of dairy cows (Berry et al., 2003; Veerkamp et al., 2001; Dechow et al., 2004), cross-sectional studies (Bastin et al., 2010; Loker et al., 2012) of Canadian dairy cows have also demonstrated a relationship between cow BCS and productivity (Loker et al., 2012), reproduction (Bastin et al., 2010), and health (Koeck et al., 2012). Despite this, cow body condition is not routinely scored in Canada by trained assessors in multiparous cows, and assessment undertaken by farmers, if undertaken at all, is known to have limited repeatability (Vasseur

Table 1. Estimation performance¹ of partial least squares regression (PLSR) and neural networks (NN) to estimate body condition score change in the 4-fold cross-validation across 305 and 120 d in milk (DIM) using just spectra, just DIM, or both DIM and spectral data together as prediction variables

Data set	Prediction variables	Method	Calibration			Validation				
			RMSE ^{2,3} (SD ^{2,3})	r (SD)	RMSE ^{2,3} (SD ^{2,3})	Bias ² (SD ²)	r (SD)	Slope (SE)	RPD (SD)	
305 DIM	Spectra only	PLSR	2.25 (0.02)	0.78 (0.001)	2.25 ^a (0.028)	0.00 ^a (0.044)	0.78 (0.004)	1.00 (0.008)	1.61 (0.01)	
		NN	1.92 (0.013)	0.85 (0.001)	1.94 ^b (0.036)	0.00 ^a (0.035)	0.84 (0.004)	1.00 (0.007)	1.87 (0.02)	
	DIM only	PLSR	1.90 (0.010)	0.85 (0.003)	1.89 ^c (0.012)	0.00 ^a (0.020)	0.85 (0.002)	1.00 (0.006)	1.92 (0.01)	
		NN	1.60 (0.013)	0.90 (0.003)	1.58 ^d (0.018)	0.00 ^a (0.020)	0.90 (0.002)	1.00 (0.007)	2.29 (0.02)	
	DIM and spectra	PLSR	1.88 (0.011)	0.86 (0.002)	1.87 ^c (0.013)	0.00 ^a (0.019)	0.86 (0.002)	1.00 (0.006)	1.94 (0.01)	
		NN	1.51 (0.011)	0.91 (0.003)	1.51 ^e (0.017)	0.00 ^a (0.013)	0.91 (0.002)	1.00 (0.005)	2.40 (0.02)	
120 DIM	Spectra only	PLSR	2.79 (0.032)	0.77 (0.002)	2.81 ^a (0.046)	-0.01 ^a (0.107)	0.77 (0.009)	1.00 (0.013)	1.57 (0.03)	
		NN	2.55 (0.025)	0.82 (0.002)	2.59 ^b (0.058)	-0.03 ^b (0.070)	0.81 (0.009)	0.99 (0.011)	1.70 (0.04)	
	DIM only	PLSR	2.09 (0.010)	0.88 (0.003)	2.08 ^c (0.023)	0.00 ^c (0.048)	0.88 (0.001)	1.00 (0.009)	2.12 (0.01)	
		NN	1.92 (0.017)	0.90 (0.004)	1.91 ^d (0.032)	0.00 ^c (0.050)	0.90 (0.003)	1.00 (0.007)	2.31 (0.03)	
	DIM and spectra	PLSR	1.98 (0.006)	0.89 (0.003)	1.98 ^e (0.030)	0.00 ^c (0.060)	0.89 (0.003)	1.00 (0.008)	2.22 (0.03)	
		NN	1.80 (0.013)	0.91 (0.003)	1.81 ^f (0.028)	0.00 ^c (0.060)	0.91 (0.002)	1.00 (0.007)	2.43 (0.03)	

¹RMSE = root mean square error; r = Pearson correlation between actual Δ BCS and estimated Δ BCS; SD = standard deviation across validation data sets; SE = standard error; RPD = ratio of the standard deviation of the BCS change variable relative to the standard error of prediction.

²Values presented are values *1,000.

³BCS units (scale 1 to 5).

^{a-f} Bias and RMSE values with different superscript within dataset are different ($P < 0.05$) from each other

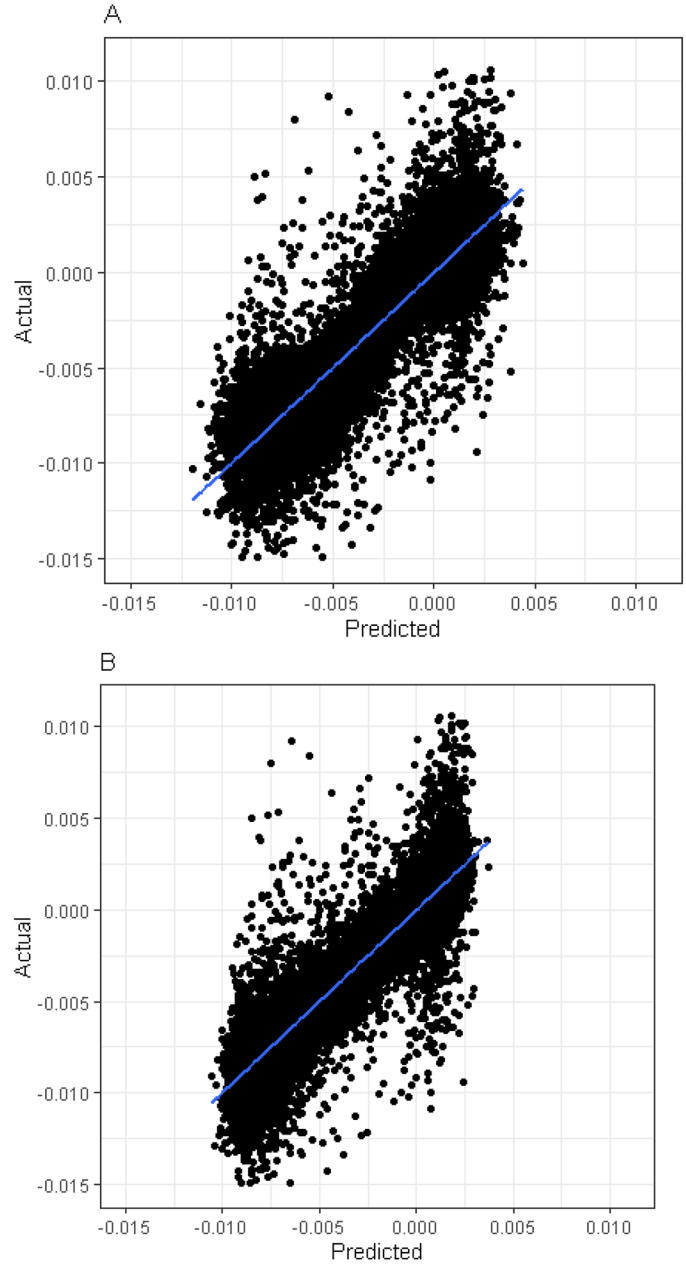


Figure 1. Scatterplot of the actual BCS change values (y-axis) vs the predicted BCS change values (x-axis) when 4-fold cross-validation using both the spectra and DIM were together used as prediction variables in the first 120 DIM for partial least squares regression (A) and a neural network (B); the slope of the line in both cases is 1.

et al., 2013). First parity Holstein-Friesian cows are, nonetheless, assessed for BCS by Holstein classifiers, and genetic evaluations for BCS is based on these records. Clearly the proven benefits of monitoring Δ BCS are not sufficient to motivate farmers to continuously body condition score cows. Hence, an alternative approach is worth considering, but such a strategy must

Table 2. Estimation performance¹ of partial least squares regression (PLSR) and neural networks (NN) to estimate body condition score change in the first 120 DIM when the equations were calibrated using data collected between the years 2017 and 2020 and validated using data collected in the year 2021 and 2022 using just spectra, just DIM, or both DIM and spectral data together as prediction variables

Prediction variables	Method	Validation				
		RMSE ^{2,3}	Bias ²	r	Slope (SE)	RPD
Spectra only	PLSR	2.81 ^a	0.32 ^a	0.76	0.97 (0.014)	1.53
	NN	2.66 ^b	0.27 ^b	0.79	0.98 (0.013)	1.62
DIM only	PLSR	2.07 ^c	0.10 ^c	0.88	0.99 (0.009)	2.08
	NN	1.89 ^d	0.09 ^c	0.90	1.00 (0.008)	2.28
DIM and spectra	PLSR	1.95 ^e	-0.02 ^d	0.89	1.00 (0.009)	2.21
	NN	1.77 ^f	-0.03 ^d	0.91	1.00 (0.008)	2.41

¹RMSE = root mean square error; r = Pearson correlation between actual Δ BCS and estimated Δ BCS; SD = standard deviation across validation data sets; SE = standard error; RPD = ratio of the standard deviation of the BCS change variable relative to the standard error of prediction.

²Values presented are values *1,000.

³BCS units (scale 1 to 5).

^{a-f} Bias and RMSE values with different superscript within dataset are different ($P < 0.05$) from each other

take cognizance of the contributing factors as to why BCS is not routinely scored on many farms.

Uptake of body condition scoring on farm

While body condition scoring is a subjective assessment of body reserves, it requires skill for proper assessment. Given this required skillset, producers may not be confident or comfortable in assessing animals. Condition scoring requires the animal to be restrained to some degree. The restraining of cows (unless tie stalls) is most convenient around milking thus impacting cow exit rate for milking as well as its impact on resource requirements during a period where resources are al-

ready stretched. While BCS in itself is informative, the relationships with reproductive performance and health are stronger with Δ BCS (Dechow et al., 2002; Bastin et al., 2010), thus requiring several BCS measures from which to generate Δ BCS.

Strategies to circumvent the necessity for body condition scoring should negate a requirement for farmer input but should also enable the estimation of Δ BCS. While farmer input is required to collect milk samples, over 6 thousand Canadian farmers already engage in routine milk testing since the information already generated has far reaching management and breeding benefits. Therefore, leveraging the information captured within the spectral pattern of milk samples to

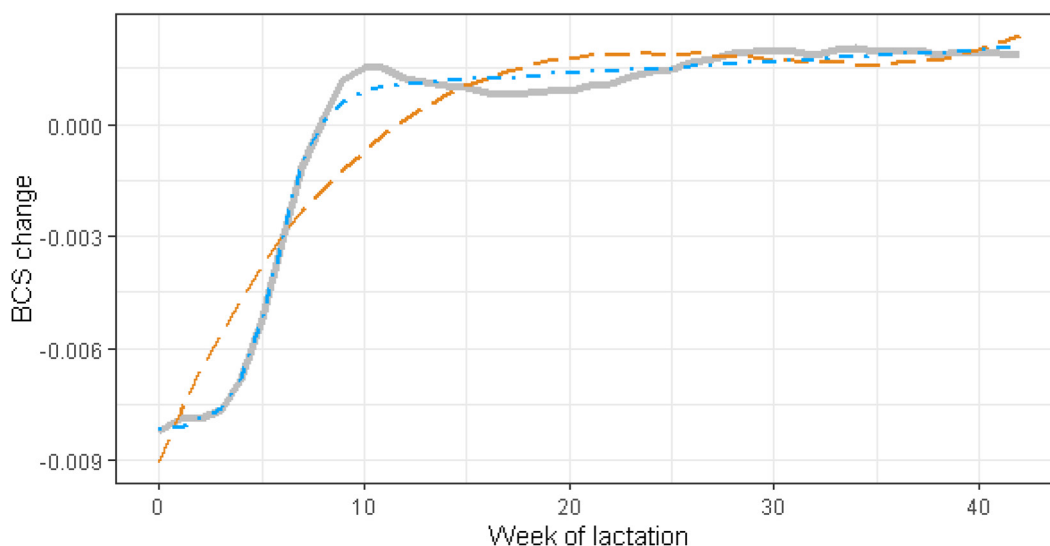


Figure 2. Body condition score (BCS) change (gray continuous line), Δ BCS estimated from partial least squares regression (orange long dashed line) and neural network (blue dot-dashed line) using DIM and spectral data up to 305 d in milk.

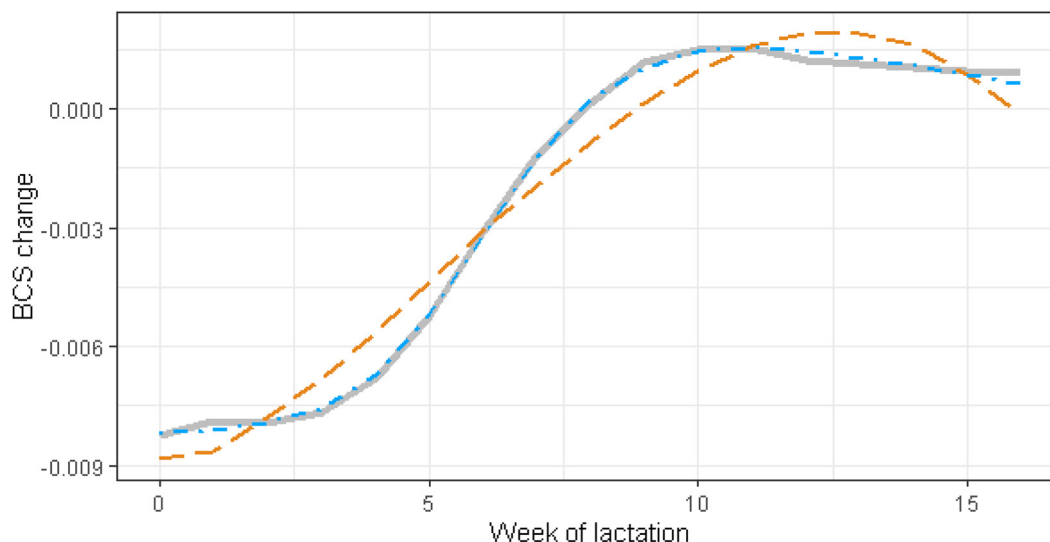


Figure 3. Body condition score (BCS) change (gray continuous line), Δ BCS estimated from partial least squares regression (orange long dashed line) and neural network (blue dot-dashed line) using DIM and spectral data up to 120 d in milk.

predict Δ BCS is a cost-effective and sensible strategy with potentially high uptake.

Options proposed to generate (Δ)BCS data include direct assessment by scorers on farm, direct prediction from digital analysis of images of cows (Mullins et al., 2019; Spoliansky et al., 2016), human assessment of images of cows (Ferguson et al., 2006), or from milk MIR (McParland et al., 2014; Frizzarin et al., 2023). The use of BCS cameras, and therefore the direct BCS prediction from digital analyses of cow images requires an initial monetary investment and routine maintenance costs for producers.

Globally, farmers routinely take milk samples of their cows which are subsequently subjected to infrared analyses in centralized laboratories with the resulting estimates of milk composition reported back to farmers. In Canada, 63.1% of the national herds and 61.4% of the Canadian cows already participate in herd testing. Internationally, Denmark is one of the countries with the greatest proportion of herds and cows recorded (90% and 89%, respectively), while New Zealand is the country with the greatest absolute number of cows recorded annually, recording over 3 million cows (76% of the total herds and 74.5% of the total cows are recorded). Results from the present study suggest that applying the developed equations using DIM and MIR combined can be used to generate estimates of Δ BCS. The beauty therefore of using milk MIR is that the spectrum already exists and therefore, once the equations and associated reports are developed, the additional costs and resources are minimal.

The equations developed in the present study to estimate Δ BCS from the milk MIR spectra can be consid-

ered accurate, as the accuracy (i.e., correlation between estimated and actual Δ BCS) was > 0.9 both across the entire lactation and within the first 120 d of lactation. Moreover, there was no bias and the slope was equal to 1. A RPD of at least 2 is often cited as an excellent model (Chang et al., 2001), albeit different thresholds have been proposed (Bellon-Maurel et al., 2010). The RPD of Δ BCS when estimated using NN surpassed this threshold of 2. Lastly, cows in different parities, of different breeds, and from different farms were used to develop the equations, increasing their robustness.

Results from the present study were compared with international studies which used cameras for the estimation of BCS in both commercial and research farms (Mullins et al., 2019; Spoliansky et al., 2016). Mullins et al. (2019) reported a correlation of 0.78 between real and estimated BCS using automated BCS cameras on 343 cows from a commercial farm while Spoliansky et al. (2016) reported a coefficient of determination of 0.75 between real BCS and estimated BCS using a 3-dimensional Kinect camera on 101 cows in a research farm (correlation of 0.87). The Fisher Z-transformation was used to compare the correlations of the previously cited studies with those from the current study. The Fisher Z-transformation transforms the sampling distribution of Pearson's r so that it becomes normally distributed. Compared with both studies which used BCS cameras for the estimation of BCS, the correlation between the actual Δ BCS and the MIR-predicted Δ BCS obtained in the present study using NN was greater ($P < 0.05$) using both the 305 DIM and the 120 DIM data set. Nonetheless, it is not surprising that perfect prediction of BCS and Δ BCS was not achievable, either in the

present study using milk MIR or from other studies using alternative technologies. This is because BCS itself is subjective and thus the gold standards (i.e., BCS and Δ BCS) include some element of uncertainty.

Usefulness of spectral data

Both in the present study and in Frizzarin et al. (2023), who estimated Δ BCS in seasonal-calving Irish dairy cows using DIM and MIR data, MIR data was included in the prediction model either on its own or together with DIM. While the predictions from just MIR data were good, there was a benefit (i.e., 16 to 33% reduction in the RMSE) by also considering DIM along with the MIR spectra in the prediction process when predicting Δ BCS records. When Δ BCS was predicted only from DIM, a mean Δ BCS value for each DIM was estimated, and therefore cows deviating from the average Δ BCS curve could not be identified. Despite this, using DIM alone in the model still achieved an acceptable accuracy of predicting Δ BCS. Indeed, in the present study, the addition of spectral data to the prediction model (additional to DIM) reduced the RMSEV (i.e., most accurate predictions) by only up to 4.6% when evaluated on the 305 DIM, and by only up to 5.5% just the first 120 DIM were considered. Moreover, using only DIM in the prediction process achieved an RPD > 2 in both the 305 and 120 DIM data set. These results are consistent with that obtained in Frizzarin et al. (2023) using 1,255 Irish dairy cows' data. Indeed, adding spectral information to a model that already included DIM reduced the RMSEV of predicting Δ BCS by up to 9% relative to just considering DIM in the model (Frizzarin et al., 2023). Not surprisingly though, when Δ BCS records deviated from the population norm (modeled by the DIM effect), models using just the MIR spectra outperformed models that included DIM (either on its own or with the MIR spectra). This implies that indeed the MIR is capturing additional information in Δ BCS, especially for those records not properly modeled by the DIM effect.

Nevertheless, to quantify the marginal information content in the MIR in predicting Δ BCS over and above just DIM, the RMSEV for predicting Δ BCS in the fastest losing BCS cows was investigated. Using the same strategy of focusing on the fastest losing 2.5% of cows, Frizzarin et al. (2023) documented a reduction in RMSEV of up to 16% when milk spectral information was added to prediction models relative to just considering DIM; the corresponding reduction in RMSEV in the present study was 7%. These results demonstrate the importance of including spectral data into the prediction model when attempting to identify cows deviating from the average Δ BCS profile.

Neural networks have clearly been documented to be a powerful statistical method to generate accurate predictions from milk MIR spectra (Denholm et al., 2020; Brand et al., 2021; Frizzarin et al., 2023). Relative to PLSR in the present study, NN reduced the RMSE by 8.5% (when using only MIR spectra in the first 120 d of lactation) to 23.8% (when using both MIR spectra and DIM across 305 d). One of the benefits of using NN is related to its ability to deal with non-linearity in relationships between the variable to be predicted and the model features. Nonetheless, PLSR is a more intuitive model and is often easier to implement, while NN requires greater computation time and an optimization of the tuning parameters which may not be optimal across different sample populations.

CONCLUSIONS

The estimation of Δ BCS in Canadian dairy cows using routinely available MIR spectral information was deemed accurate, particularly in early lactation which is arguably the most important period of the lactation profile. While Δ BCS could be accurately predicted from just DIM, considering also milk spectral data (along with DIM) in the prediction model improved the predictions, especially when identifying cows deviating from the population norm was of interest. The proposed methodology can be readily used to estimate the Δ BCS of individual cows concomitant with the already existing estimation of cow milk composition thus providing animal-specific information on its energy status at no additional cost. Therefore, the estimated Δ BCS using milk MIR spectra can be useful for inclusion in breeding programs (e.g., as a correlated trait in a multi-trait genetic evaluation) as well as aiding in day-to-day farm management.

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Genomics, Genome Quebec, and Genome British Columbia. As per the research agreement, researchers maintain independence in conducting their studies, own their data, and report the outcomes regardless of the results. The decision to publish the findings rests solely with the researchers

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