Reassessing Wiggans' Method for Estimating Daily Yields in 3× Milking Systems over Four Decades: What Have We Learned?

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Abstract

More than forty years have passed since Wiggans (1986) proposed a least-squares approach to derive multiplicative yield correction factors from proportional yields in cows milked three times daily. In the present study, we re-evaluated these correction factors using 3× milking data collected from 2023 to 2025 across four Holstein dairy farms in three U.S. states. The objectives were twofold: to assess the validity of the existing yield factors and to examine the robustness of the associated modeling strategies. We evaluated the accuracy of estimated daily yields using out-of-sample validation, allocating approximately 50% of records to training and the remaining 50% to testing. Accuracy measures included the correlation between observed and estimated 24-h yields, mean absolute error, and mean squared error. We observed clear shifts in model parameters over the past four decades, indicating greater dynamic responsiveness of proportional yield to interval length, while baseline section-specific effects have become less important. Nevertheless, improvements in the accuracy of estimated daily yields were modest. Substantial variability was observed among farms, suggesting that herd-level factors—such as management practices, milking system precision, and data consistency—contribute more to predictive performance than temporal changes in model parameters. Expanding the training dataset, particularly by including more representative herds and cow-day records, may enhance predictive stability and generalizability. Although imposing a 24-h normalization constraint improves model interpretability and ensures the coherence of proportional estimates, it does not necessarily yield meaningful gains in predictive accuracy. Overall, this study reaffirms the continued relevance of proportional-yield modeling and existing correction factors as practical benchmarks, while providing updated empirical guidance for estimating daily yields in three-times-daily milking systems.

Keywords: accuracy, Holstein, fat, milk, protein, yield correction factors

Introduction

Milking frequencies vary among farms and occasionally by season. In the U.S., the Dairy Herd Improvement (DHI) program routinely records only one (or sometimes two) of the day's milkings. However, herds that adopt twice- or thrice-daily milking still require consistent, unbiased estimates of 24-hour yields from partial milking records for accurate recordkeeping, genetic evaluations, and management decisions.

To address this need, Wiggans (1986) proposed an ordinary least-squares (OLS) approach with *a posteriori* rescaling of the intercepts to estimate yield correction factors by modeling proportional yields in cows milked

three times daily. Notably, this method is among those officially adopted in the U. S. through the National Dairy Herd Improvement (DHI) program. It has also been formally incorporated into the ICAR Guidelines (ICAR, 2022) as a standard procedure for computing 24-hour milk, fat, and protein yields from partial milking records (DeLorenzo and Wiggans, 1986; Liu et al., 2000).

In this study, we re-evaluated yield correction factors using 3X milking data collected from 2023 to 2025 at four Holstein dairy farms across three U.S. states. The objectives are twofold: to assess the validity of the existing yield factors and to examine the robustness of the associated statistical methods.

Materials and Methods

Statistical models

Let y_{ij} denote the proportional daily yield of the *j*-th milking for the *i*-th cow, and t_{ij} represent the corresponding milking interval (h). Wiggans (1986) assumed a linear relationship between these two variables:

$$y_{ij} = \alpha_j + \beta t_{ij} + e_{ij}. \quad (1)$$

where α_j is the intercept for milking *j*, β is the common regression coefficient across all three milkings, and e_{ij} is the residual effect.

The non-zero, intercept α_j values represent section-specific offsets that quantify the model-estimated yield proportion at $t = 0$ for each milking, which is merely a mathematical construct rather than a biological reality.

The common regression coefficient β indicates that the rate of change in proportional yield per additional hour of interval is the same across all milkings. Hence, biological differences among milkings are captured by their distinct intercepts.

Furthermore, Wiggans (1986) proposed correcting the intercepts to a 24-hour basis after fitting the model. For $t_{i1} + t_{i2} + t_{i3} = 24$,

$$\sum_{j=1}^{3} \hat{\alpha}_j = 1 - 24\hat{\beta}. \quad (2)$$

Mathematically, the difficulty with this form of *a posteriori* rescaling lies in the non-uniqueness of the solution. The imposed scaling constraint yields only one equation, yet three intercept parameters must be estimated, even when the regression coefficients are fixed.

One arbitrary approach is to define equal deviation adjustment of the intercepts across the three milkings, that is,

$$\delta = \frac{1}{3}\left(1 - \sum_{j=1}^{3} \hat{\alpha}_j - 24\hat{\beta}\right),$$

such that

$$\alpha_j^* = \hat{\alpha}_j + \delta = \hat{\alpha}_j + \frac{1}{3}\left(1 - \sum_{j=1}^{3} \hat{\alpha}_j - 24\hat{\beta}\right) \quad (3)$$

Then, summing the three intercepts confirms that the equality constraint (2) is satisfied.

Nevertheless, the above adjustment of the intercepts is statistically suboptimal. The key issue is that the constraint is not imposed during model estimation, but only afterward. As a result, the final adjusted parameters do not minimize the residual sum of squares under the constraint. Instead, we propose an alternative approach that incorporates the constraint directly during model fitting. This specification avoids the unrealistic extrapolation to $t = 0$ and reduces collinearity between the intercept and interval terms.

Specifically, in a 3× milking system, we define an 8-h interval as the physiological and management baseline. Deviations from this interval are interpreted as positive or negative shifts in proportional yield. Under this model setting, the intercepts reflect systematic differences among milkings at the baseline interval, whereas the slope quantifies the change in yield proportion per hour of deviation from the 8-h reference.

When the totality of a 24-hour daily milking interval holds precisely, i.e., $t_{i1} + t_{i2} + t_{i3} = 24$, the constraint for the intercepts becomes:

$$\sum_{j=1}^{3} \hat{\alpha}_j = 1. \quad (4)$$

In matrix notation, the reparameterized model can be expressed as follows:

$$\boldsymbol{y} = \mathbf{X}\boldsymbol{b} + \boldsymbol{e}, \quad (5)$$

where $\boldsymbol{y}$ is a vector of proportional daily yields and $\boldsymbol{e}$ is the residual vector.

The design matrix (X) and the parameter vector (b) are defined as follows:

$$\mathbf{X} = \begin{bmatrix} 1 & 0 & 0 & t_{i1} - 8 \\ 0 & 1 & 0 & t_{i2} - 8 \\ 0 & 0 & 1 & t_{i3} - 8 \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}; \boldsymbol{b} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \beta \end{bmatrix}.$$

The equality constraint on the intercepts is implemented as follows:

$$\boldsymbol{cb} = d, \quad (6)$$

where $\boldsymbol{c} = (1 \quad 1 \quad 1 \quad 0)$ and $d = 1$.

Mathematically, this formulation represents a quadratic programming problem with a linear equality constraint, and its solution is given by:

$$\widehat{\boldsymbol{b}} = \widehat{\boldsymbol{b}}_0 - (\mathbf{X}'\mathbf{X})^{-1}\boldsymbol{c}'(\boldsymbol{c}(\mathbf{X}'\mathbf{X})^{-1}\boldsymbol{c}')^{-1} \times \left(\boldsymbol{c}\widehat{\boldsymbol{b}}_0 - d\right) \quad (7)$$

where $\widehat{\boldsymbol{b}}_0 = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\boldsymbol{y}$ is the unconstrained OLS estimator, and

$$\delta = (\mathbf{X}'\mathbf{X})^{-1}\boldsymbol{c}'(\boldsymbol{c}(\mathbf{X}'\mathbf{X})^{-1}\boldsymbol{c}')^{-1}\left(\boldsymbol{c}\widehat{\boldsymbol{b}}_0 - d\right)$$

is the adjustment term.

The variance-covariance matrix of the constrained estimator is:

$$var\left(\widehat{\boldsymbol{b}}\right) = \sigma^2[(\boldsymbol{X}'\boldsymbol{X})^{-1} - (\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{c}'(\boldsymbol{c}(\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{c}')^{-1}c(X'X)^{-1}]$$

Here, σ^2 is the residual variance from the constrained OLS model.

The constrained OLS model can also be implemented through reparameterization. Let

$$\alpha_3 = 1 - \alpha_1 - \alpha_2. \quad (8)$$

Substituting Equation (8) into model (1) and rearranging the terms to group coefficients by unknown parameter yields:

$$y_{ij} = (x_{i1} - x_{i3})\alpha_1 + (x_{i2} - x_{i3})\alpha_2 + x_{i3} + \beta t_{ij} + e_{ij}.$$

where x_{ij} is a dummy variable which equal 1 if the partial yield is observed or 0 otherwise.

Moving x_{i3} to the left-hand side as a part of the data gives:

$$y_{ij} - x_{i3} = (x_{i1} - x_{i3})\alpha_1 + (x_{i2} - x_{i3})\alpha_2 + \beta t_{ij} + e_{ij}.$$

The re-parameterized model can thus be expressed as:

$$y_{ij}^* = x_{i1}^*\alpha_1 + x_{i2}^*\alpha_2 + t_{ij}\beta + e_{ij}, \quad (9)$$

where $y_{ij}^* = y_{ij} - x_{i3}$, $x_{i1}^* = (x_{i1} - x_{i3})$, and $x_{i2}^* = (x_{i2} - x_{i3})$.

The parameter values, α_1, α_2, and β, in model (9) can then be obtained using OLS. Finally, the third intercept (α_3) is recovered from Equation (8).

Analyzing 3X milking data

Milking data were collected from 2023 to 2025 at four 3× milking Holstein dairy farms (A, B, C, and D) across three U.S. states. Milkings were classified by start time: 1 (02:00 to 09:59 h), 2 (10:00 to 17:59 h), or 3 (18:00 to 01:59 h). Milkings were recorded weekly for each cow up to 120 days in milk, then monthly until 305 days or the end of lactation. Data cleaning removed duplicate, missing, and incomplete records, leaving 15,702 × 3 (Farm A), 13,574 × 3 (Farm B), 8,515 × 3 (Farm C), and 10,821 × 3 (Farm D) milking observations.

Four models were evaluated: constrained OLS (CLS); reparameterized OLS (RLS), which is algebraically equivalent to CLS; the Wiggans (1986) model fitted with historical parameter estimates (WLS0); and the Wiggans (1986) model refitted to the current data (WLS1). The accuracy of the estimated yields was assessed using out-of-sample validation, with approximately 50% of the records allocated to training and the remaining 50% to testing; each validation was repeated ten times. Accuracy measures included the correlation between observed and predicted 24-h yields, mean absolute error (MAE), and mean squared error (MSE).

Results and Discussion

Estimation of model parameters

The CLS and RLS produced identical model parameters across all three traits, confirming that the two formulations are mathematically equivalent (Table 1). Also see Figure 1. Under the CLS specification, we consistently observed that $\hat{\alpha}_1 + \hat{\alpha}_2 + \hat{\alpha}_3 \approx 1$, indicating that the estimated daily yields are properly confined to a 24-h period.

In contrast, WLS1, which implemented the Wiggans (1986) approach, yielded parameter estimates substantially different from those of CLS and RLS, even though all three models fit the same data. Nevertheless, WLS1 can still be viewed as an approximately equivalent representation of the CLS model after an

algebraic transformation. To illustrate, consider the CLS equation for proportional milk yield at the first milking:

$$y = 0.334 + 0.0381 \times (t - 8)$$
$$= (0.334 - 0.0381 \times 8) + 0.0381 \times t$$
$$\approx 0.0292 + 0.0381t.$$

Table 1: Estimated model parameters from recently collected milking data, compared with the old estimates by Wiggans in 1986 [1,2]

Method	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\alpha}_3$	$\hat{\beta}$
		Milk yield		
RLS	0.334	0.332	0.334	0.0381
CLS	0.334	0.332	0.334	0.0381
WLS1	0.029	0.028	0.029	0.0381
WLS0	0.077	0.068	0.066	0.0329
		Fat yield		
RLS	0.336	0.338	0.326	0.0246
CLS	0.336	0.338	0.326	0.0246
WLS1	0.139	0.142	0.129	0.0246
WLS0	0.186	0.186	0.182	0.0186
		Protein yield		
RLS	0.332	0.334	0.334	0.0390
CLS	0.332	0.334	0.334	0.0390
WLS1	0.020	0.022	0.021	0.0390
WLS0	0.072	0.065	0.063	0.0333

[1] CLS = constrained ordinary least squares; RLS = reparameterized CLS; WLS0 = Wiggans (1986) model fitted to historical data; WLS1 = Wiggans (1986) model fitted to current data.
[2] Values in the table are means across ten replicates.

This equation closely matched the WLS1 equation for the first milking, yielding identical intercepts and regression coefficients. The same was true for the equations for fat and protein.

When comparing the Wiggans (1986) model fitted to the current dataset (WLS1) with the model fitted to the historical data (WLS0), we observed clear shifts in model parameters over the past four decades: intercept estimates based on the recent data were much smaller, and the regression coefficients were larger than those reported in 1986.

The intercept parameter α_j represents a section-specific offset that captures systematic milking effects not explained by interval length (e.g., diurnal management routines or preparation differences). In the Wiggans (1986) model, because the intercept corresponds to the predicted proportional yield at $t = 0$, which lies outside the biologically meaningful range of milking intervals, its absolute magnitude should not be interpreted literally. Instead, the relative differences among intercepts reflect persistent structural differences among milkings that are not attributable to interval length.

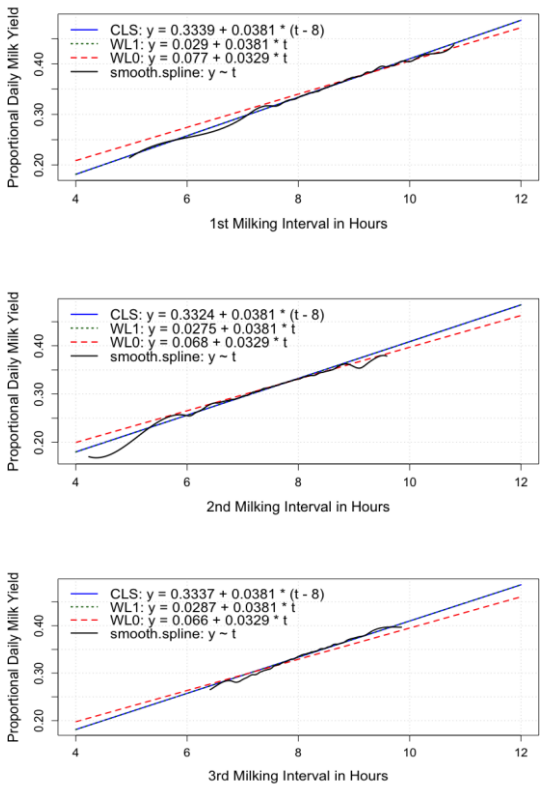


Figure 1. Illustration of linear regression models and smoothing splines for proportional daily yields over the milking interval (in hours): 1st milking (left); 2nd milking (middle); 3rd milking (right).

Across all three traits, intercept estimates for the three milkings were substantially lower (27.9–76.4%) in the current dataset than in the historical dataset. This reduction in between-section variability suggests that structural differences among the three milkings may have diminished over time, possibly due to more standardized management routines, improved milking-system precision, and more consistent cow handling.

It is noted that part of the observed reduction in intercept magnitudes is also mathematically consistent with an increase in the regression coefficient $\hat{\beta}$ under the imposed 24-h constraint,

$\sum_{j=1}^{3}\hat{\alpha}_j = 1 - 24\hat{\beta}$. Increasing the regression coefficient $\hat{\beta}$ necessarily reduces the sum of intercepts $\sum_{j=1}^{3}\hat{\alpha}_j$ in order to maintain the 24-h equility constraint. Thus, a portion of the smaller intercept value may reflect an algebraic consequence of the higher slope estimate: a larger regression coefficient mechanically forces a lower intercept.

The regression coefficient $\hat{\beta}$ represents the marginal change in proportional yield per additional hour of the milking interval. For milk yield, this coefficient rose from 3.29% per hour in 1986 to 3.81% per hour in the current dataset. Similarly, the per-hour change increased from 1.86% to 2.46% for fat yield and from 3.33% to 3.90% for protein yield. In relative terms, the largest increase was in protein yield (132.3%), followed by fat (117.1%) and milk (115.8%).

From a biological perspective, a larger $\hat{\beta}$ value indicates that proportional yield has become more responsive to interval length than it was four decades ago. Several factors likely contribute to this shift. Improvements in milking preparation, adoption of automatic take-off systems based on milk flow, and enhanced milking completeness may have reduced residual milk, thereby strengthening the proportional relationship between milk accumulation and elapsed time. In addition, long-term genetic selection and improved nutrition have increased milk secretion rates and cisternal storage capacity, making milk accumulation more linear and more tightly coupled to interval length.

A mathematical explanation is as follows. Let $S(t)$ denote the cumulative milk secretion since the previous milking, and let the daily yield be $Y = S(t_1) + S(t_2) + S(t_3)$. The proportional yield for a given milking is

$$y(t) = \frac{S(t)}{Y}.$$

If secretion were strictly linear over the relevant interval (6–12 h), then $S(t) \approx rt$, where r is the secretion rate. In that case,

$$y(t) \approx \frac{rt}{r(t_1+t_2+t_3)} = \frac{t}{24},$$

Hence, under the linear proportional yield model, the "theoretically perfect" slope is $1/24$ (4.17%) per hour for all three traits. In practice, however, milk accumulation rates deviate from perfect linearity due to residual milk, incomplete udder emptying, and temporary storage limitations. In the present study, the observed slopes were all smaller, ranging from 59.0% (fat) to 91.4% (milk) and 93.5% (protein) relative to the "perfect" slope.

Instead, a more general representation is

$$S(t) = rt - \delta(t),$$

where $\delta(t)$ captures nonlinear effects such as carryover or incomplete removal. Then, the derivative of proportional yield with respect to interval length is

$$\frac{dy}{dt} = \frac{S'(t)}{Y} = \frac{rt-\delta(t)}{24r-\Delta}$$

where $t_1 + t_2 + t_3 = 24$ and $\Delta = \delta_1(t_1) + \delta_2(t_2) + \delta_3(t_3)$.

Now, expand around the "ideal" case $\delta'(t) = 0$ and $\Delta = 0$. Using

$$\frac{1}{24r-\Delta} = \frac{1}{24r} \cdot \frac{1}{1-\Delta/(24r)} \approx \frac{1}{24r}\left(1+\frac{\Delta}{24r}\right)$$

for small $\Delta/(24r)$, we get

$$\frac{dy}{dt} \approx (r - \delta'(t)) \cdot \frac{1}{24r}\left(1+\frac{\Delta}{24r}\right)$$
$$= \frac{1}{24}\left(1-\frac{\delta'(t)}{r}\right)\left(1+\frac{\Delta}{24r}\right). \qquad (10)$$

In the above, the factor $\left(1-\frac{\delta'(t)}{r}\right)$ captures local nonlinear effects over interval t. If $\delta'(t) > 0$, meaning that nonlinear losses (e.g., residual milk or incomplete removal) increase with interval length, this term is less than 1, and the slope is reduced below $1/24$. Conversely, if nonlinear distortion diminishes, the slope approaches the ideal value.

The factor $\left(1+\frac{\Delta}{24r}\right)$ captures global day-level effects, where $\Delta = \sum_{j=1}^{3}\delta_j(t_j)$ represents total nonlinear deviation across the day. Because Δ enters through the denominator $Y = 24r - \Delta$, it adjusts the proportional scaling of secretion relative to total daily yield.

Hence, assuming ideal linear secretion with no nonlinear effects ($\delta'(t) = 0$ and $\Delta = 0$), we obtain $\frac{dy}{dt} = \frac{1}{24} = 0.0417$, meaning that the proportional yield increases exactly in proportion to time. In reality, the observed slope depends on the contrast between $\frac{\delta'(t)}{r}$ and $\frac{\Delta}{24r}$.

Our results suggest $\frac{\delta'(t)}{r} > \frac{\Delta}{24r}$ for the three traits. The larger the contrast, the smaller the regression coefficient will be. Consider a special case where $\frac{\delta'(t)}{r} \equiv \frac{\Delta}{24r}$. Then, we will always observe that $\frac{dy}{dt} \leq 0.417$.

Accuracy of estimated daily yields

The accuracy of yield estimates from different models is shown in Table 2. When fitted to the recent data, all models produced nearly identical accuracy measures for the three traits. The correlation between actual and estimated daily yields was 0.906 for milk, 0.833 for fat, and 0.885 for protein yield. MSE was approximately 3.03 kg for milk, 0.183 kg for fat, and 0.094 kg for protein.

MSE followed a pattern similar to MAE across models. Because the actual total daily milking interval was close to 24 hours (23.9 h for Herd 1, 24.2 h for Herd 2, 23.6 h for Herd 3, and 24.2 h for Herd 4), the 24-h normalization constraint had little practical impact on predictive performance, regardless of whether it was imposed during model fitting or applied a posteriori. Therefore, when the sum of observed intervals already approximates 24 h, enforcing the unity constraint on proportional yields produces only negligible adjustments to the fitted values.

From a statistical perspective, the constrained OLS estimator retains the best linear unbiased estimator (BLUE) property when the imposed constraint is correctly specified, which, however, does not guarantee a marginally globally minimized MSE. However, if the constraint is misspecified, the resulting estimator becomes biased because the true parameter vector does not lie within the constrained parameter space. Even when the constraint is valid, our results indicate that empirical gains in predictive accuracy are minimal. Under these considerations, the 24-h adjustment of intercepts may not be strictly necessary in practice, as its efficiency gains are modest and contingent upon the correctness of the imposed restriction. Omitting the 24-h constraint in the Wiggans (1986) framework would simplify implementation protocols (e.g., ICAR, 2022) for computing daily milk, fat, and protein yields from partial milking records.

Table 2. Accuracy of estimated milk, fat, and protein yields using different methods [1,2,3]

Traits	Metrics	RLS	CLS	WLS1	WLS0
MY	COR	0.906	0.906	0.906	0.904
	MAE	3.03	3.03	3.03	3.08
	MSE	21.7	21.7	21.7	22.1
FY	COR	0.833	0.833	0.833	0.831
	MAE	0.183	0.183	0.183	0.184
	MSE	0.071	0.071	0.071	0.072
PY	COR	0.885	0.885	0.885	0.883
	MAE	0.094	0.094	0.094	0.957
	MSE	0.020	0.020	0.020	0.022

[1,2] CLS, RLS, WLS0, and WLS1: see Table 1 for the abbreviations and explanations;
[3] Correlation = correlation between the estimated and actual daily yields; MAE = mean absolute error of the estimated yield; MSE = mean squared error of the estimated yield.

Over the past four decades, models fitted to current data generally achieved better fit on the training data, but only slightly higher corrections and lower errors (MAE and MSE) than those based on historical data. These results likely reflect the inherent two-step nature of such a proportional-yield modeling strategy. A better-fitting model yields a more accurate average projection of proportional yield over the milking interval. However, the estimated yield is obtained in the second step using the so-called "multiplicative yield correction factor" (Wu et al., 2022), and its accuracy depends on variations in partial yields.

Direct evidence comes from the marked differences in estimated yields across farms. Across ten replicate runs, the correlation between observed and estimated 24-h milk yields was 0.946 - 0.948 for Farm B, 0.905 - 0.910 for Farm A, and 0.890 – 0.895 for Farms C and D. In contrast, Farm A had a higher accuracy for fat yields (0.861–0.862) than the other three herds (0.792–0.804). Farm A also had higher correlations for fat protein yields (0.920–0.921) than the other three farms (0.859 – 0.874).

These large differences among farms indicate that model performance is strongly shaped by herd-level factors, including management consistency, milking-system precision, and data quality. Herds with more uniform milking intervals, accurate sensor calibration, and consistent cow-handling practices tend to produce more stable proportional-yield patterns, resulting in higher correlations and lower prediction errors. Conversely, greater variability in milking timing, equipment performance, or cow movement introduces additional noise into the proportional-yield relationship, thereby reducing model accuracy.

Given the substantial heterogeneity across the four Holstein herds, it is not surprising that models fitted to the current data only marginally outperformed those based on historical parameters. Between-herd variability in management practices, milking systems, and data quality likely contributed more to prediction error than temporal shifts in the proportional-yield relationship, particularly with a limited number of herds. In contrast, the historical dataset (Wiggans, 1986) comprised 47,495 cow-days across 65 herds. Hence, including more herds may have produced more stable parameter estimates by averaging over a wider range of management conditions.

Conclusions

We observed clear shifts in model parameters over the past four decades. The intercept estimates from recent data were smaller, whereas the regression coefficients were larger than those reported in 1986. This pattern indicates that the dynamic responsiveness of proportional yield to interval length has increased over time, while baseline section-specific effects have become relatively smaller.

Despite these changes in parameter estimates, improvements in daily yield accuracy were modest. However, substantial variability across farms suggests that herd-level factors—such as management practices, milking system precision, and data consistency—contribute more to predictive performance than temporal changes in model structure. Expanding the training dataset, particularly by including more representative herds and cow-day records, may further improve predictive stability and generalizability. Imposing a 24-h normalization constraint improves model interpretability and ensures coherent proportional estimates, but it does not necessarily improve predictive accuracy.

Overall, this study reaffirms the ongoing relevance of proportional-yield modeling and existing correction factors as practical benchmarks and offers updated empirical guidance for estimating daily yields in three-times-daily milking systems.

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