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Economic evaluation of stall stocking density of lactating dairy cows

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ABSTRACT

An increase in stall stocking density (SSD), as measured by the number of lactating cows per stall in a freestall barn, reduces cow performance, such as milk yield and fertility, but may increase farm profitability. Our objectives were to calculate effects of varying SSD on profit per stall for a range of effects on cow performances and external farm factors and store results in regression metamodels. The literature on quantified effects of SSD on cow performance that directly affects cash flow was found to be weak. We assumed effects of SSD on milk yield, probability of conception, and probability of culling. External farm factors were probability of insemination, feed price, and milk price. A herd budget-simulation model was used which mimics the performance of cows in a herd and calculates profit per stall per year and other results. The SSD varied from 100 (no overstocking) to 150% (severe overstocking) in steps of 10%. Sensitivity analyses for effects of SSD on cow performance and effects of external farm factors were performed. Three regression metamodels were developed. The first metamodel accurately predicted profitability at 100% SSD for all variations in the external farm factors. Optimal SSD varied from 100 to 150% SSD, depending on the combination of inputs, and was very sensitive to changes in the size of the milk loss and milk and feed prices. Average optimal SSD of all 2,187 combinations of inputs was 120% SSD and average maximum increase in profit was $99/stall per year. Of the 2,187 combinations of inputs, 18% were ascending (maximum increase in profit >150% SSD), 33% were descending (maximum profit at 100% SSD), and 50% had a maximum increase in profit between 100 and 150% SSD. The second metamodel accurately captured changes in profit for all combinations of biological and external inputs and SSD. A third metamodel captured breakeven daily milk losses which would result in the same profit as at 100% SSD given the same external farm factors. In conclusion, overstocking was profitable under plausible economic conditions in the United States. The 3 metamodels accurately captured the results for a wide range of values of the input variables. A tradeoff will occur between economically optimal SSD and animal welfare in some situations.

Key words: overcrowding, stocking density, profit, economics

INTRODUCTION

Stocking density on dairy farms is a quantitative measure of the concentration of dairy animals. It may be measured by the surface area per cow, feed bunk space per cow, or the number of cows per stall in a freestall barn [stall stocking density (**SSD**)]. In the current study we focus on the economics of SSD of lactating dairy cows because the literature on effects of SSD on cow performance appears to be stronger than the literature on other measures of stocking density. Overstocking in this context occurs when SSD >100%.

Cows are categorized as allelomimetic, meaning they want to express the same behavior at the same time (Barrows, 2001). This behavior includes the need to lie down or the need to eat when returning from the milking parlor. When stocking density is (too) high, the behavioral needs of the cow may not be met because other cows are in the way. This can negatively affect her health and performance and, hence, her economic performance. For example, Grant (2011) reported that significant overcrowding reduces feeding activity, alters resting behavior, and decreases rumination activity. In a review of 8 studies, Krawczel (2012) reported that lying time seemed to seriously decrease when the SSD was greater than 120%. In a designed experiment, Fregonesi et al. (2007) observed a reduction in lying time from 12.9 down to 11.2 h/d when SSD increased from 100 to 150%. Cook (2002) suggested that environments that increase the proportion of cows standing, and thus reducing the lying time to less than 10 to 11 h daily, put cows at risk of developing lameness and other health problems.

Significant overcrowding reduces milk production (Bach et al., 2008; Grant, 2011). Krawczel (2012) reported a study that found that first-parity cows

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comingled with older cows were more affected by overstocking than older cows. Also, in that study, the lame cows in the pen suffered greater losses in milk yield than the healthy cows when SSD increased. In a survey on modernized Wisconsin dairy barns, Bewley et al. (2001) did not find statistically significant differences in annual rolling average milk production and feed intake between different stocking densities. Krawczel and Grant (2009) summarized studies that suggested milk fat slightly reduced whereas SCC tended to increase with greater SSD. Schefers et al. (2010) reported that, based on observations in large commercial dairy farms in the Midwest United States, fertility decreased with increased stocking densities.

The fixed costs of freestall barns may make it economically attractive to increase the stocking density past the level where cow behavioral needs are best met. In a survey of modernized Wisconsin dairy barns conducted in 1999, the average SSD was 108% (Bewley et al., 2001). Four-row barns had, on average, greater SSD than 6-row barns (111 vs. 104%). Farmer satisfaction with cow comfort, milk production, and feed intake was consistent across all overcrowding categories. That study also found that barn costs per cow were the lowest in barns that had 121 to 130% SSD, but barn costs per stall were quite similar. The 2007 Dairy Survey (USDA-NAHMS, 2010) showed that 41% of US freestall operations had an average SSD ≥104%. In a survey of cow comfort of high-producing Holstein dairy cows in 121 North American freestall dairy farms, von Keyserlingk et al. (2012) reported that 60% of dairy farms had a SSD >100% (range = 71–197%); hence, overstocking of dairy cows is not uncommon. Lusk and Norwood (2011) illustrated the tradeoffs between farm profitability and animal welfare at different stocking densities for laying hens. We did not find economic evaluations of SSD in dairy freestall barns.

Stocking density economics follow the classical law of diminishing marginal returns (Lusk and Norwood, 2011). This means that each additional cow will generate revenues (milk sales, calf value, cull sales) at costs that vary with the cow (variable costs: costs for feed, some parlor supplies, maybe some labor). Costs that are not affected (fixed costs) by the number of cows in the pen (e.g., depreciation and most of the labor costs when SSD varies moderately) do not affect the economically optimal SSD. Every additional cow also reduces the performance of the other cows already in the pen. The economic optimal SSD is reached when the marginal returns of the pen equal the marginal costs of the pen. At this SSD, the profit per stall is maximized. Adding another cow to the pen past the optimal SSD implies that the pen's marginal returns are less than its marginal costs and profit per stall decreases.

Optimal economic SSD may be calculated with an economic simulation model. Results will depend on several input variables with varying values, such as prices and assumed effects of SSD on cow performance. In sensitivity analysis, often one-factor-at-a-time designs are used to vary single inputs while holding other inputs constant. Such designs greatly limit the number of evaluated scenarios that can be reported. A larger number of combinations of inputs may be of interest (e.g., because effects of SSD on cow performance are somewhat uncertain), but reporting all results in tables or figures is not feasible. Metamodels are models of models that aim to simplify the relationship between the inputs and outputs of a simulation model (Friedman, 1996; Jalal et al., 2013). Examples of metamodels using regression applied to livestock science models include Vonk Noordegraaf et al. (2003), who modeled prevalence of infectious bovine rhinotracheitis for different control strategies, and Kristensen et al. (2008), who modeled gross margin as a function of technical performance indicators of dairy herds. These metamodels are then easily applied without the need for making the original simulation model available.

Our first objective was to evaluate the effects of SSD of lactating dairy cows on farm profitability. This includes finding the economically optimal SSD for a variety of different effects of SSD on cow performances (milk yield, probability of conception, culling). The economically optimal SSD may also depend on external farm factors, such as milk or feed prices. A second objective was to capture the results of many combinations of inputs with regression metamodels such that these results can be easily approximated without the simulation model used in the current study.

MATERIALS AND METHODS

Herd Budget Model

We updated and expanded an existing herd budget model (Lima et al., 2010) for our economic analyses. Briefly, the herd budget model mimics the technical and economic performance of a herd of young stock and cows. Animal flow through the herd is modeled by Markov chains, which determine the daily probability an animal is in a state characterized by parity, days since calving, and days pregnant. Approximately 732,000 states for cows are possible, depending on the length of the insemination period. Transition from state to state is calculated by the probabilities of culling, conception, abortion, and calving. Technical performance in a state is determined by technical inputs such as milk production curves, feed intake functions, BW, probabilities of insemination, conception, abortion, and culling, as well

Table 1. Default technical and economic inputs for the herd budget model

Variable	Source or value
Lactation functions	Based on Dematawewa et al. (2007)
Feed intake functions	Based on NRC (2001)
BW functions	Based on De Vries (2006)
Probability of culling	Based on Lima et al. (2010)
Voluntary waiting period	60 d
Last insemination opportunity	First parity 350 d, later parities 300 d
21-d service rate	60%
Probability of conception	40%
Probability of abortion	10%
Semen cost ($/insemination)	$15
Milk price ($/kg)	$0.45
Lactating feed cost ($/kg of DM)	$0.35
Calf sale prices ($/head)	Dairy male $50, dairy female $200
Cull price ($/kg of BW)	$1.70
Other variable costs ($/cow per d)	$2.00
Fixed costs ($/stall per d)	$2.00

as management inputs such as lengths of the insemination period and dry period. Economic performance in a state is calculated from the technical performance and economic inputs such as prices of milk, culled and sold animals, feed, and various other variable costs. Fixed costs that only vary with the number of stall are included to allow calculation of realistic total costs per cow. Finally, herd outputs are calculated by summations of the multiplication the technical and economic performance in each state by the fraction of animals in that state. One such output is dairy farm profit. In the model, herd demographics and outputs are always in a deterministic steady state because the probability of each state remains constant over time given a set of inputs. Changes in any of the inputs result in immediate recalculation of steady state results. The herd budget model was developed in Excel (Microsoft, Redmond, WA).

For this study, dairy farm profit was expressed per stall per year. A stall is a freestall in a freestall barn containing lactating cows. The number of stalls for dry cows were assumed to be unlimited and are not relevant for this study. Fixed costs vary with the number of stalls, but the number of stalls was kept constant. By definition, variable revenues and variable costs varied with the number of cows as described earlier. All revenues (milk sales, calf values, cull sales) were assumed variable. Variable costs included feed costs, insemination costs, replacement costs, still birth and dystocia costs, and other variable costs such as for labor and parlor supplies.

We based our inputs for this study (Table 1) on our knowledge of plausible values for US dairy herds during the last several years, partly motived by data reported by DRMS (2015). Important inputs were varied in the sensitivity analysis to investigate their effect on SSD economics as described below. Our assumptions and therefore results were independent of the number of stalls on a farm.

Modeled Effects of Stall Stocking Density on Cow Performance

Stall stocking density could affect milk production, reproduction, and culling in the herd budget model based on a review of the literature and our assumptions. First, Bach et al. (2008) studied the effects of stocking density and other nondietary factors in 47 dairy herds (approximately 3,129 lactating cows) from the northeast of Spain that were offered the same lactating ration. After correction for other nondietary factors, the authors found a linear loss in milk yield of 0.52 kg/d per 10% increase in SDD measured in the range from 83 to 167%. Alternatively, Grant (2011) reported a negative relationship of 1.68 kg/d for each hour of reduced lying time from experiments in the US Combining Grant's data with the reduction in lying time due to overcrowding from Fregonesi et al. (2007); the result is that cows lose about 0.57 kg/d per 10% increase in SSD, which is similar to that of Bach et al. (2008). In our simulation, we therefore reduced milk production by 0.50 (default), 0.75, or 1.00 kg/d per cow per 10% greater SSD. The 0.75- and 1.00-kg/d losses are greater than the losses reported in the literature but might include other not well quantified effects, such as increased lameness or lower milk quality. Second, the probability of conception was reduced by 0.1 percentage points per 10% increase in SSD (default), as found by Schefers et al. (2010) for large commercial dairy farms in the Midwest United States. Reductions by 0 and 0.2 percentage points in probability of conception were also evaluated. Third, increases in the relative probability of culling of 0 (default), 0.1, and 0.2 percentage points per 10% increase in SSD were evaluated based on anecdotal evidence, although no literature regarding SSD and culling was found.

The biological losses as a result of overstocking were assumed to be the same for all parities in the model. The effects on milk production, probability of conception, and probability of culling, each at 3 levels, varied linearly with SSD; all $3^3 = 27$ combinations of these biological effects were evaluated. Stall stocking density was varied from 100 to 150% in steps of 10 percentage points.

In the herd budget model, lower milk production reduced DMI and therefore reduced feed costs. Dry matter intake was otherwise independent of SSD. Lower probabilities of conception resulted in longer days open, increased reproductive culling, and, hence, affected the herd demographics with their associated revenues and costs. Increased probabilities of culling also changed herd demographics and annual cow replacement costs. Dry cow performance was assumed not affected by SSD. The number of dry cows depended on the number of lactating cows. The number of lactating cows depended only on SSD.

Sensitivity Analyses

Three sensitivity analyses were carried out to reveal how profitability of variations in SSD depended on the external factors milk price, feed price, probability of insemination, and fixed versus variable costs. In the first sensitivity analysis, the evaluated milk prices were \$0.40, \$0.45 (default), and \$0.50/kg of milk. Evaluated feed prices were \$0.30, \$0.35 (default), and \$0.40/kg of DM for lactating cows. The probabilities of insemination were 40, 60 (default), and 80%. Variable other costs were \$1, \$2 (default), and \$3 per cow per day. Fixed cost per stall per day were \$4 minus variable other costs. Therefore, the sum of variable other costs and fixed costs remained constant at 100% SSD; all $3^4 = 81$ combinations of these external effects were evaluated for the 27 combinations of biological effects. In the first sensitivity analysis the full factorial of $3^7 = 2{,}187$ scenarios was evaluated for each of the 6 SSD, resulting in 13,122 evaluations with the herd budget model.

In the second sensitivity analysis, we created 1,000 scenarios of randomly selected input values between the minimum and maximum of each of the biological and external input variables. We evaluated each scenario at each of the 6 SSD. This resulted in 6,000 evaluations. We used these 1,000 scenarios to test the goodness-of-fit of the full-factorial regression metamodel A developed on the data from the first sensitivity analysis (explained below).

The third sensitivity analysis included finding the break-even milk losses for the 6 other (not milk loss) input variables ($3^6 = 729$ scenarios), with SSD varying from 110 to 150%, resulting in 3,645 evaluations. These break-even milk losses resulted in the same profit per stall per year as the 100% SSD for each of the 729 scenarios. Therefore, the change in profit per stall per year (**dprofit**) from the 100% SSD evaluation was \$0 for each SSD in the same scenario. Break-even milk losses were found with the goalseek function in Excel because the relationship between milk loss and profitability in the herd budget model is nonlinear.

Metamodeling

We created 3 regression metamodels. Metamodel A captured the profit per stall per year at 100% SSD for the variations in milk price, feed price, and probability of insemination (27 scenarios) in the first sensitivity analysis. Metamodel B captured the change in profit per stall per year as a function of the 8 variables (3 biological and 4 external effects, as well as SSD) in the first sensitivity analysis. Metamodel C captured the break-even milk loss for SSD >100% calculated in the third sensitivity analysis. We also regressed dprofit onto SSD for each scenario to see how well the response in dprofit to SSD could be fit by a low order polynomial equation.

We used the GLMSELECT procedure of SAS 9.3 (SAS Institute Inc., Cary, NC) to find the best-fitting regression equations as metamodels. The main goal of the regression metamodels was prediction and not interpretation of the individual effects. Possible effects were limited to main effects, quadratic effects, and 3-way interactions of the variables. Stepwise regression was used with the PRESS stop criterion to determine which effects remained in the model. There was no limit on the number of allowed effects in metamodel A. For metamodels B and C, the number of allowed effects in the final models ranged from 5 to 35. Goodness of fit was expressed as the root of the mean squared error (**RMSE**), prediction errors of single evaluations, bias, and the coefficient of determination of the final equation. The RMSE is a single measure of predictive power of a regression equation. Prediction errors were calculated as the actual observation from the herd budget model minus the predicted observation from the regression metamodel.

RESULTS

No Overstocking

Based on the default inputs and with a 100% SSD, results per stall per year were \$5,307 milk sales, \$442 cull sales, \$167 calf value, \$2,973 feed costs, \$845 replacement costs, and \$867 variable other costs. Fixed

Table 2. Technical and economic results for the herd budget model with default assumptions for inputs and effects of stall stocking density (SSD) on cow performance[1]

	SSD					
Item per stall per year	100%	110%	120%	130%	140%	150%
Milk sales ($)	5,307	5,747	6,170	6,576	6,965	7,338
Cull sales ($)	442	490	538	587	638	689
Calf sales ($)	167	183	199	216	232	249
Feed cost ($)	2,973	3,244	3,511	3,773	4,030	4,282
Replacement costs ($)	845	937	1,029	1,124	1,220	1,319
Variable other costs ($)	867	954	1,040	1,127	1,213	1,300
Fixed costs ($)	730	730	730	730	730	730
Profit ($)	500	555	596	626	642	645
Number of calvings	1.22	1.34	1.46	1.58	1.69	1.81
Milk yield (kg)	11,794	12,770	13,710	14,613	15,478	16,306
Milk/cow per d (kg)	28.48	28.06	27.64	27.22	26.80	26.38
21-d pregnancy rate (%)	19.2	18.8	18.4	18.0	17.5	17.1
Annual cull rate (%)	37.3	37.6	37.9	38.2	38.6	38.9

[1]Default SSD effects: 0.5 kg/cow per d decrease in milk yield per 10% increase in SSD, 0.1 percentage point lower probability of conception per 10% increase in SSD, no effect of SSD on probability of culling.

costs were $730, and profit was therefore $500. Further, annual milk yield was 11,794 kg, daily milk yield per lactating cow was 32.3 kg, 21-d pregnancy rate was 19%, and annual cow cull rate was 37%. Profit per stall per year for the 27 combinations of milk prices, feed prices, and probabilities of insemination at 100% SSD ranged from −$568 to $1,558. Milk sales minus feed cost per 100 kg of milk varied from $4.97 to $28.30.

The regression metamodel A predicting profit per stall per year at 100% SSD was: −2011.2 + 11,328 × milk price + 947.29 × milk price × probability of insemination − 7,996.2 × feed price − 566.33 × milk price × feed price × probability of insemination. The RSME of this model was $7.64, coefficient of determination was 0.9998, and prediction errors ranged from −$6.96 to $11.66. For the default inputs, predicted profit per stall per year was $490, resulting in a prediction error of $10.

When metamodel A was applied to the data set created in the second sensitivity analysis (random inputs, 100% SSD only, 1,000 evaluations), the bias was $5.42; standard deviation of the prediction errors was $4.72, with minimum and maximum prediction errors of −$5.84 and $11.79. Thus, metamodel A also provided good estimates of profit per stall per year for the randomly chosen external farm factors values within the ranges of the sensitivity analysis.

Variations in SSD

Table 2 shows technical and economic herd statistics for the 6 SSD for the scenario with default inputs in the first sensitivity analysis. All sales, variable costs, and profit per stall per year increased with increasing SSD in this scenario. The dprofit was $145 when SSD increased from 100 to 150%. As expected, milk per cow per day and 21-d pregnancy rate decreased with greater SSD. The annual cull rate slightly increased as a result of the lower reproductive efficiency, which led to a slightly greater culling risk of nonpregnant cows.

For each scenario in the first and second sensitivity analysis, the relationship between dprofit and SSD could be described by a concave quadratic equation with nearly perfect fit (maximum prediction error <$1). From these quadratic equations, the optimal SSD was calculated at the maximum dprofit between 100 and 150% SSD. Average optimal SSD of the 2,187 scenarios in the first sensitivity analysis was at 120% SSD and average maximum dprofit across all scenarios was $99. Average dprofit at 120% SSD was $20 across all scenarios. In the first sensitivity analysis, 384 (18%) scenarios were ascending (maximum dprofit >150% SSD), 716 (33%) were descending (maximum dprofit <100% SSD), and 1,087 (50%) scenarios had a maximum dprofit between 100 and 150% SSD. Optimal SSD in these last 1,087 scenarios was 122% and average dprofit was $65.

The marginal value of SSD around the optimal SSD was near $0 (a flat dprofit curve around the optimum SSD). In the scenarios that peaked between 100 and 150% SSD, dprofit decreased by on average $10 when the SSD was 10 percentage points greater or smaller than the optimum SSD. The range was a loss between $4 and $16/stall per year.

The optimal SSD and dprofit were very sensitive to changes in the size of the milk loss and milk prices, as illustrated in Table 3 for 9 scenarios. Using the default milk price, at a loss of 0.50 kg/cow per d, the maximum dprofit was $145 at 148% SSD. At losses of 0.75 and 1.00 kg/cow per d, the optimal SSD were 118 (dprofit =

Table 3. Effects of milk loss, milk price, and stall stocking densities (SSD) on change in profit (dprofit; $/stall per year)[1]

Milk loss[2] (kg/d)	Milk price ($/kg)	Maximum dprofit (optimum SSD)	dprofit at 5 SSD[3]				
			110%	120%	130%	140%	150%
0.5	$0.40	6 (110%)	6	0	−15	−43	−81
0.5	$0.45	145 (148%)	54	96	125	142	145
0.5	$0.50	371 (150%)	103	192	266	326	371
0.75	$0.40	0 (100%)	−21	−57	−109	−177	−260
0.75	$0.45	29 (118%)	23	29	15	−17	−67
0.75	$0.50	145 (137%)	67	114	139	144	127
1.0	$0.40	0 (100%)	−47	−114	−202	−310	−439
1.0	$0.45	0 (100%)	−8	−39	−95	−175	−278
1.0	$0.50	38 (117%)	32	36	13	−39	−117

[1]Default SSD effects: 0.5 kg/cow per d decrease in milk yield per 10% increase in SSD, 0.1 percentage point lower probability of conception per 10% increase in SSD, no effect of SSD on probability of culling.

[2]Milk loss per 10% increase in SSD.

[3]dprofit is $0 at 100% SDD.

$29) and 100% (dprofit = $0), respectively. When the milk price was $0.40/kg, the optimal SSD were lower than at higher milk prices because the pen's increase in milk yield is worth less. Similarly, greater milk prices lead to higher optimal SSD and greater dprofit.

The effects of the changes in probability of culling on optimal SSD were small. In the scenario with default inputs, increases in the probabilities of culling of 0, 10, and 20% resulted in optimal SSD of 148, 144, and 141%, respectively; when the milk price was $0.40/kg, the optimal SSD were 110, 108, and 106% respectively. These ranges were slightly smaller when milk loss was 0.75 or 1.00 kg/d.

Increases in feed cost reduced the optimal SSD, but the effect of a change of $0.05/kg of DM on the optimal SSD was smaller than a change in $0.05/kg of milk because each kilogram greater DMI resulted in approximately 1.4 kg more milk. Increases in variable other costs also reduced the optimal SSD. An increase of $1/d variable other costs had the similar effect on the optimal SSD as a decrease of $0.04/kg of milk when average milk yield was 28 kg/d.

The effects of changes in probability of insemination on optimal SSD were much smaller than the effect of changes in milk prices. In the scenario with default other inputs, probabilities of insemination of 40, 60, and 80% resulted in optimal SSD of 141, 148, and 150%, respectively; when the milk price was $0.40, the optimal SSD were 103, 110, and 115%, respectively. These ranges were slightly smaller when milk loss was 0.75 or 1.00 kg/d.

Metamodeling of Variations in SSD

We captured the dprofit for each of the 6 SSD of the 2,187 scenarios in the first sensitivity analysis with 5 regression metamodels that varied in the number of parameters allowed. The first metamodel including only the main effects of the 7 biological and external input variables and SSD and SSD^2 had a large RSME of $108 and coefficient of determination of 0.6860. Fit statistics of 4 other metamodels that allowed for 3-way interactions of the 7-input variables and SSD and SSD^2, but were limited to 5, 15, 25, or 35 parameters, are shown in Table 4. The metamodel with 25 parameters had noticeably better fit than the models with fewer parameters, but the gain from the 35-parameter metamodel was small. In the 35-parameter model (metamodel B, Table A1), bias was <0.001, RMSE was $2.5, and coefficient of determination was >0.999. The minimum and maximum prediction errors for the 13,122 evaluations in the first sensitivity analysis were −$7 and $10. Regression models allowing for greater than 3-way interactions or >35 parameters resulted in only minor improvements in the goodness of fit (data not shown). We also judged the 35-parameter metamodel to be sufficiently accurate for our predictions.

When metamodel B was applied to the 6,000 evaluations of the second sensitivity analysis (random inputs), the bias was $1.86; standard deviation of the prediction errors was $2.1, with minimum and maximum prediction errors of −$4 and $9. Thus, metamodel B also provided accurate estimates of dprofit at the 6 SSD for randomly chosen inputs.

The predicted optimum SSD using metamodel B were very similar to the optimum SSD found when separate quadratic equations were applied to each of the 2,187 individual scenarios calculated in the first sensitivity analysis. For example, the standard deviation of the differences between the optimal SSD predicted by metamodel B and calculated with the herd budget model was 0.4 percentage points, with a minimum of −1.5 to 2.1 percentage points; the bias was 0.11 percentage points.

Break-Even Milk Yield Changes

In the third sensitivity analysis, break-even milk yield changes ranged from −1.76 to 0.37 kg/cow per d per 10% increase in SSD to obtain the same profit per stall per year as at 100% SSD. The greatest decrease in milk yield occurred where the marginal value of an additional cow was the greatest (high milk price, low feed price, low other variable cost, and SSD was 110%); profit per stall per year was then high. The greatest increase in milk yield was needed when the marginal value of an additional cow was negative and profit per stall per year was negative, which also occurred at a SSD of 110%. Increases in milk yield from greater SSD are unlikely to occur in reality.

Total milk change is the change in daily milk yield regardless of SSD that results in the same profit per stall per year as 100% SSD. Figure 1 shows total milk changes for the 3 milk prices evaluated and the default values for the other inputs at varying levels of SSD. For example, a 130% SSD and a decrease of 1.38 kg/d results in the same profit per stall per year as a 100% SSD and no decrease in milk yield when the milk price was \$0.40/kg. Total break-even milk yield decreased more with higher milk prices (\$0.50 vs. \$0.40) and greater SSD (150%). The largest total milk yield decrease was 6.45 kg/cow per d, when SSD was 150% and dprofit was the highest. The most positive total milk change was an increase of 1.68 kg/cow per d. In this case, the SSD was 150% and the marginal value of an additional cow was negative.

Metamodeling of Break-Even Milk Yield Changes

Metamodel C captured the total milk loss as a function of SSD and the 6 input variables (all input variables except milk loss; Table A2) in the third sensitivity analysis. Metamodel C was constrained to include 35 parameters as a balance between accuracy of prediction and size of the metamodel. The RMSE was 0.068 kg/cow per d, coefficient of determination was 0.9980, and the bias was <0.0001. Minimum and maximum prediction errors were −0.24 and +0.19 kg/cow per d. In both cases, prediction errors were <11% of the total change in milk yield calculated by the herd budget model. Metamodels A, B, and C are available online in a Microsoft Excel 2013 spreadsheet (Supplemental data; http://dx.doi.org/10.3168/jds.2015-10556).

DISCUSSION

The main aim of our study was to evaluate the effect of varying SSD in a freestall barn on profitability per stall. The results should be interpreted with caution because the literature on effects of SSD on cow performance other than behavior is limited. Quantitative relationships between variations in SSD and cow performance are scarce. Published effects of variations in stocking density are sometimes obtained from cross-sectional studies where it may be difficult to control for other factors that differ on the surveyed farms. Alternatively, designed experiments with varying short-term stocking densities may not fully capture the long-term effects of overstocking. Most studies evaluated SSD less than 150%. We included only linear effects of varying SSD on cow performance, whereas a nonlinear effect of SSD might be expected. For example, in a review of 8 studies, Krawczel (2012) reported a nonlinear effect of stocking density on reduction in lying time. The perfect quadratic fit of dprofit as a function of SSD for each combination of inputs is the result of the assumed linear effects of SSD on milk loss, probability of conception, and probability of culling.

The herd statistics under the default assumptions (Table 1) reflected our chosen input values to represent a plausible (typical) US dairy herd (e.g., DRMS, 2015). The extensive sensitivity analyses aimed to represent a wide range of US dairy herds as well as possible effects of variations in SSD on cow performance.

Table 4. Fit statistics for the best 5-, 15-, 25-, and 35-parameter regression metamodels chosen from 7 variables and up to 3-way interactions to predict change in profit per stall per day (dprofit) as a function of stall stocking density in the data set of the first sensitivity analysis[1]

Item	5	15	25	35[2]
R^2	0.731	0.993	>0.999	>0.999
Correlation prediction/actual	0.855	0.997	>0.999	>0.999
Bias	<0.001	<0.001	<0.001	<0.001
Root mean square error	100.0	15.9	2.7	2.5
Minimum prediction error	−391	−78	−11	−7
Maximum prediction error	459	82	11	10

[1]Seven variables included milk loss, probability of conception, probability of culling, probability of insemination, milk price, feed price, and variable cost.

[2]Metamodel B in this study.

To overcome some of the concerns about underestimating the effects of SSD in the literature, we evaluated 3 levels of changes in milk yield, as well as calculated break-even milk yield losses that would result in the same profitability as when SSD was 100%. Greater effects of SSD on probability of conception and increases in culling were also evaluated. We did not investigate the economic response to SSD within subgroups of cows (e.g., per parity or pregnancy status) when similar cows are grouped together. For example, some evidence exists that milk production decreases in older cows are less than in younger cows when both groups are commingled (Krawczel, 2012), which implies that the optimal SSD for older cows may be greater than for younger cows. Future studies might evaluate other relationships between SSD and cow performance, such as greater effects of SSD on culling, fertility, and more limited effects on DMI.

Optimal SSD were very sensitive to reasonable changes in milk prices and feed prices. Optimal SSD increased when marginal cows were more profitable at 100% SSD. The corollary is that SSD should be reduced when milk sales minus feed costs decrease, which is typical during periods with low milk prices. The probability of insemination and effects of SSD on culling had minor effects on the optimal SSD. Economically, the optimal SSD was ≥100% in 67% of the scenarios we evaluated (1,471/2,187) and ≥120% in 42% of the scenarios.

Whereas overstocking may be warranted economically under plausible assumptions, overstocking decreases animal welfare. Based on observations of primarily cow behavior, Krawczel and Grant (2009) recommended that SSD should not exceed 120%. Several measures of welfare are also reduced when SSD increases past approximately 120% (Moore, 2010). Legislation or acceptable animal husbandry practices may prevent (severe) overstocking. We did not attempt to combine both economic and welfare implications of overstocking in a multiobjective optimization of SSD to determine a recommended level of SSD.

We also did not attempt a probabilistic sensitivity analysis of input values to determine the most likely optimal economic SSD. Instead, stocking density characteristics for 2,187 scenarios were evaluated and captured with regression metamodels. The size of a metamodel is a tradeoff between the number of parameters and accuracy of prediction. Metamodel B for dprofit and the optimal SSD appeared to provide sufficiently accurate predictions for the 7 input variables and SSD within the minimum and maximum values for each input. Notice that the effects of milk and feed prices can be linearly extrapolated outside of the price ranges evaluated in our study. The optimal SSD can be found for each scenario by taking the first derivative with respect to SSD from the regression metamodel B. Another way is to plot dprofit for various SSD given all other inputs and observe the SSD at the maximum.

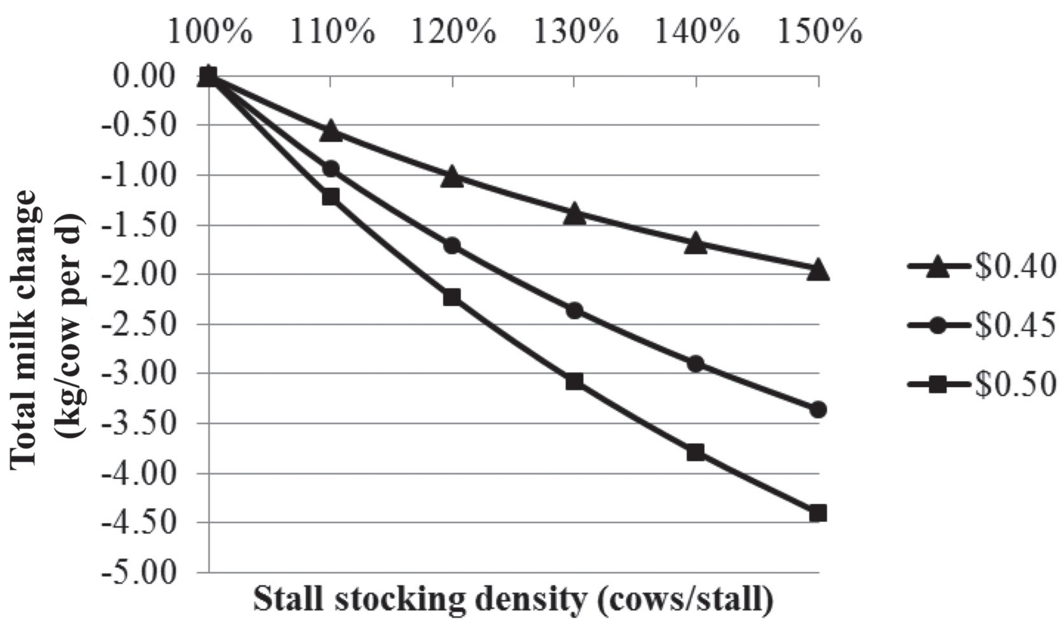

Figure 1. Break-even total milk changes per cow per day for 3 milk prices ($/kg of milk) and default values for the other inputs. All stall stocking densities result in the same profit/stall per year given a milk price.

The metamodels also allow for calculating milk prices at which overstocking is no longer profitable.

Break-even changes in milk yield were also reasonably accurately captured with metamodel C. These break-even milk yields may be approximated by holding the total milk yield in the freestall barn constant and then calculating decreases in milk yield per cow when cows are added. However, feed efficiency and reproductive efficiency, and therefore the marginal value of milk, change when SSD changes. Therefore, break-even profit analyses based on milk yield alone are less accurate.

Metamodeling using regression equations was fairly successful in our study as judged by analysis of the prediction errors. Improvements to the goodness of fit might be made by, for example, applying transformations to input variables or creating more regression equations to capture relationships in sub-datasets. Other methods for metamodeling have also been used, such as machine learning (e.g., Jalal et al., 2013; Shahinfar et al., 2014). An advantage of a regression metamodel is that the equation can be published and can easily be built into a spreadsheet or other software.

One assumption in our study was that other physical factors were not affecting cow performance when SSD was varied. In practice, overcrowding at the stalls likely also increases competition at the feed bunk. Studies that investigated effects of increasing SSD on milk production, for example, may inherently have included some effects due to more limiting feed bunk space per cow, but these associations are not clear. Feed bunk stocking density may often be more limiting in 3-row pens and for transition cows than SSD. For example, Nordlund et al. (2006) believed that feed bunk space per cow is vastly more important as a risk factor for transition cow ketosis than SSD, because the most important underlying factor in fresh cow disease is decreased DMI. Explicit effects of various feed bunk stocking densities on cow performance were not captured in our study, which further cautions the interpretation of our results.

CONCLUSIONS

Many studies exist that document the effects of (short-term) overstocking on cow behavior, but quantitative measures of overstocking on factors that affect cow cash flow directly (such as milk yield, fertility, and lameness) are scarce. The economically optimum SSD was quite sensitive to milk and feed prices. Overstocking may be profitable under plausible economic conditions in the United States. Stall stocking density should be reduced when milk sales minus feed cost per cow decrease to maximize profit per stall. We developed 3 regression metamodels that accurately predicted profit per stall per year, change in profit, optimal SSD, and break-even milk yield for a wide range of values of the input variables. A tradeoff will occur between economically optimal SSD and animal welfare in some situations.

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Appendix

Table A1. Parameters of the final 35-parameter regression metamodel B to predict change in profit per stall per year as a function of stall stocking density and 7 input variables[1]

Parameter	Value
Intercept	555.4104
SSD	−556.884
Cullloss	73.28483
SSD*SSD2*cullloss	−48.132
SSD*pconcloss	−65.1464
SSD*SSD2*pconcloss	155.4083
SSD2*cullloss*pconcloss	−14.0398
Milkprice	−11,373.5
SSD*milkprice	11,375.87
SSD*milkloss*milkprice	−3,460.22
SSD2*milkloss*milkprice	3,458.69
SSD2*cullloss*milkprice	−50.6888
SSD*pconcloss*milkprice	−1,435.01
SSD2*pconcloss*milkprice	1,287.949
Varcost	365.0111
SSD*varcost	−365.006
Pinsem	−98.8002
SSD*pinsem	101.2921
SSD2*cullloss*pinsem	−43.5621
SSD*pconcloss*pinsem	210.8391
SSD2*pconcloss*pinsem	−249.156
milkprice*pinsem	−637.324
SSD*milkprice*pinsem	641.0897
Feedprice	8,089.51
SSD*feedprice	−8,176.72
SSD2*feedprice	78.43678
SSD*milkloss*feedprice	1,199.899
SSD2*milkloss*feedprice	−1,210.15
SSD2*pconcloss*feedprice	−264.567
pconcloss*milkprice*feedprice	421.7833
pinsem*feedprice	104.7218
SSD2*pinsem*feedprice	−98.8958
milkloss*pinsem*feedprice	21.25217
cullloss*pinsem*feedprice	105.8866
pconcloss*pinsem*feedprice	125.5131

[1]SSD = stall stocking density (100 to 150%); SSD2 = SSD*SSD; cullloss = increase in daily probability of culling per 10% increase in SSD (0 to 20%); pconcloss = decrease in probability of conception per 10% increase in SDD (0 to −20%); milkloss = milk loss per 10% increase in SSD (kg/cow per d, −0.5 to −1); pinsem = probability of insemination (40 to 80%); feedprice = feed price ($/kg of DM, 0.35 to 0.45); milkprice = milk price ($/kg of milk, 0.40 to 0.50); varcost = variable other costs ($/cow per day, $1 to $3).

Table A2. Parameters of the final 35-parameter regression metamodel C to predict break-even total milk change as a function of stall stocking density and 6 input variables[1]

Parameter	Value
Intercept	10.56281
SSD	4.350154
SSD2	−15.401
SSD*SSD2*cullloss	0.38527
SSD*SSD2*pconcloss	−1.55948
Milkprice	66.14257
SSD*milkprice	−126.444
SSD2*milkprice	60.71502
cullloss*milkprice	−0.9215
pconcloss*milkprice	−2.06234
SSD*pconcloss*milkprice	4.48784
Varcost	−2.17743
SSD2*varcost	1.724573
milkprice*varcost	7.906326
SSD*milkprice*varcost	−6.67328
Pestrus	1.215613
SSD2*pinsem	−1.2706
SSD2*cullloss*pinsem	0.145372
SSD2*pconcloss*pinsem	1.038439
milkprice*pinsem	6.226004
SSD*milkprice*pinsem	−12.3313
SSD2*milkprice*pinsem	6.184119
pconcloss*milkprice*pinsem	−2.30975
Feedprice	−58.8246
SSD2*feedprice	73.62822
SSD*SSD2*feedprice	−14.0186
pconcloss*feedprice	21.29553
SSD*pconcloss*feedprice	−29.2613
SSD2*pconcloss*feedprice	9.303095
milkprice*feedprice	72.62433
SSD2*milkprice*feedprice	−72.4799
varcost*feedprice	−15.7139
SSD*varcost*feedprice	27.16529
SSD2*varcost*feedprice	−9.87568
milkprice*varcost*feedprice	−4.11607

[1]For each set of input variables, profit per stall per year is the same for any stall stocking density. SSD = stall stocking density (100 to 150%); SSD2 = SSD*SSD; cullloss = increase in daily probability of culling per 10% increase in SSD (0 to 20%); pconcloss = decrease in probability of conception per 10% increase in SDD (0 to −20%); pinsem = probability of insemination (40 to 80%); feedprice = feed price ($/kg of DM, 0.35 to 0.45); milkprice = milk price ($/kg of milk, 0.40 to 0.50); varcost = variable other costs ($/cow per day, $1 to $3).