

Potential of Using New Technology for Estimating Body Condition Scores

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Abstract

Although the benefits of body condition scoring (BCS) are intuitive to most dairy industry professionals, relatively few dairy farms have incorporated it as part of their routine management strategy. The lack of adoption of this technique is largely attributable to subjectivity and time requirements. An automated BCS system would be less demanding of time by trained personnel, less stressful to cattle, more objective and consistent, and possibly more cost effective. The technical feasibility of utilizing digital images (IceScore, Ice Robotics Ltd., Midlothian, UK) to determine BCS was assessed for lactating dairy cows at the Scottish Agricultural College (SAC) Crichton Royal Farm. Up to 23 anatomical points were manually identified on dorsal images (N = 3332) captured automatically from above as cows passed through a weigh station. All identifiable points were utilized to define and formulate measures describing the cow's contour. Hook angle and posterior hook angle were significant predictors of BCS ($P < 0.05$), and 100% of predicted BCS were within 0.50 points of actual BCS and 93% were within 0.25 points. The economic feasibility of investment in an automated BCS system was also explored using a dynamic, stochastic simulation dairy model designed to examine investments in dairy intervention technologies. The model was created in Microsoft Excel using the @Risk add-in to consider the stochastic nature of key variables with Monte Carlo simulation. Benefits of the BCS system were

considered by estimating potential improvements resulting from technology adoption through reduced disease incidence, reduced days open, and increased energy efficiency. The simulation resulted in a series of net present values used to identify the probability of observing a positive net present value. Future efforts should explore ways to facilitate extraction of information from images automatically using a larger number of animals to accurately predict scores of cows across all levels of BCS. With further development and refinement, automated BCS may become an integral part of decision making on modern dairy farms with applications in nutrition, genetics, and animal well-being.

Introduction

Although the benefits of regular BCS are intuitive to most dairy producers, nutritionists, and consultants, relatively few dairy farms have incorporated it as part of their dairy management strategy (Hady et al., 1994). There are many reasons for the lack of adoption of this system, mostly related to its subjectivity and the time commitment required. These concerns have led to a search for alternative means of assessing body energy reserves in cattle. Coffey et al. (2003) proposed that automatic recording of BCS would increase its usefulness for dairy herd management and conjectured that BCS obtained from images could be at least as good, if not better than, traditional BCS at assessing body lipid content.

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Despite success with other species, few research groups have approached the idea of automatic body condition scoring in dairy cattle (Coffey et al., 2003; Leroy et al., 2005; Pompe et al., 2005). An automated BCS system would be preferred to observational scoring because it would require less time, be less stressful on the animal, be more objective and consistent, and possibly more cost effective (Leroy et al., 2005). Thus, we set out to explore the technical and economic feasibility of automation of BCS using digital images.

Materials and Methods

Digital imaging

Data for this study were collected at the Scottish Agricultural College Crichton Royal Farm in Dumfries, Scotland, UK from September to November 2006 (Bewley et al., 2008). Scores were obtained weekly using 2 different BCS systems which are the primary systems utilized within the United Kingdom (Lowman et al., 1976; Mulvany, 1977) and the United States (Edmonson et al., 1989; Ferguson et al., 1994). The Lowman/Mulvany (**UKBCS**) system involves palpation of specific body parts using a 0 to 5 scale with 0.25 intervals. The Edmonson/Ferguson (**USBCS**) system is based entirely upon visual assessment using a 1 to 5 scale with 0.25 intervals. The UKBCS were assessed by 2 experienced employees of the farm in a permanent weigh station as cows left the milking parlor following the a.m. milking. The USBCS were assessed by a visiting scientist from the United States trained in BCS using the flowcharts developed by Ferguson et al. (1994). Within-cow outliers were removed for both systems by comparing BCS obtained during the successive week. After these edits, means were 2.12 (± 0.35) and 2.89 (± 0.40), modes were 2.25 and 2.75, and ranges were 1.0 to 3.5 and 1.5 to 4.5 for the UKBCS ($n = 2346$) and USBCS ($n = 2571$), respectively.

Black and white images were collected using a digital camera placed above the permanent weigh station. The camera pointed downward toward and approximately 60 to 70 cm above the cows' backs. The camera was stationary and remained at the same height throughout the duration of the project. The weigh station was located in an exit alley from the parlor within an enclosed barn with minimal artificial lighting. When the rear gates of the weigh station closed after cow entry, the camera was triggered to capture an image from the cow in the station. Relative to collection of subjective BCS on the day of the week where scores were collected, image collection occurred simultaneously with UKBCS and prior to USBCS. Images were identified with a timestamp and stored for subsequent analysis. Image timestamps were matched with weigh station timestamps to identify the cows being photographed. Although the herd was milked 3 times per day, images were generally only available for the early p.m. milking because of lighting limitations at the a.m. and late p.m. milkings.

Twenty-three anatomical points, corresponding to identifiable features, were classified for potential influence on BCS (Figures 1 and 2). A computer program was created to identify these points on the collected images. With this program, image files are loaded, and points are identified manually and visually with the click of a computer mouse. When the point has been identified, an x/y coordinate corresponding to this point is recorded in a separate text file. If a point is not discernible on a particular image, that point is set to missing. Any image where both hooks were not clearly visible was considered to be of insufficient quality and no points were recorded. Points were selected moving clockwise around the cow, starting with the left forerib (facing the cow) and ending with the right forerib. An edit was performed on the data to remove any points that did not follow this pattern. When all 23 points were identified, the x/y coordinates created an outline of the cow (Figure 2). Distances between points on opposite sides of

the cow were calculated (e.g. right hook to left hook) as measures of width at various points. These points were also used to calculate angles reflecting the shape of the contour of the cow. Fifteen angles around the hooks, pins, and tailhead were calculated when points were available in this manner (Figure 3).

For each image, 7 composite anatomical angles were calculated using the mean of opposing angles from the cow's left and right sides. For example, a composite hook angle was calculated as the average of left and right hook angles. Similarly, a coefficient of variation was calculated corresponding to each of the composite angles for each image. Cutoff values for outlier removal of these composite angles were created using the mean \pm 3 standard deviations (**SD**) of these coefficients of variation across the entire data. When the coefficient of variation corresponding to an individual image composite angle was greater than or less than these cutoff values, the respective composite angle was removed. The objective of this edit was to remove angles where the left and right angles were considerably different, likely indicative of the cow standing diagonally within the weigh station, a poor quality image, or gross errors in point identification.

A weekly average of each composite angle, along with tailhead angle, was calculated for each cow/week combination. Weekly averages with less than 2 composite hook angles were removed from the data set prior to model creation. The MIXED procedure of SAS[®] (Cary, NC) was used to analyze models for prediction of BCS using the angles obtained from the images. These models were performed as a repeated measures analysis with variables repeated by week with cow as the random subject. All composite angles were considered in preliminary models, but only effects significant at $P < 0.05$ are included in the models reported here. The model included 834 and 767 observations for USBCS and UKBCS, respectively.

Economic analysis

A simulation model of a dairy enterprise was developed to evaluate the economics of investments in Precision Dairy Farming technologies by examining a series of random processes over a 10-year period. The model was designed to characterize the biological and economical complexities of a dairy system within a partial budgeting framework by examining the cost and benefit streams coinciding with investment in a Precision Dairy Farming technology. Although the model currently exists only in a research form, a secondary aim was to develop the model in a manner conducive to future utility as a flexible, farm-specific decision making tool. The basic model was constructed in Microsoft Excel 2007 (Microsoft, Seattle, WA). The @Risk 5.0 (Palisade Corporation, Ithaca, NY) add-in for Excel was utilized to account for the random nature of key variables in a Monte Carlo simulation. In Monte Carlo simulation, random drawings are extracted from distributions of multiple random variables over repeated iterations of a model to represent the impact of different combinations of these variables on financial or production metrics (Kristensen and Jorgensen, 1998). The basic structure of the model is depicted in Figure 4.

The underlying behavior of the dairy system was represented using current knowledge of herd and cow management with relationships defined from existing literature. Historical prices for critical sources of revenues and expenses within the system were also incorporated as model inputs. The flexibility of this model lies in the ability to change inputs describing the initial herd characteristics and the potential impact of the technology. Individual users may change these inputs to match the conditions observed on a specific farm.

After inputs are entered into the model, an extensive series of intermediate calculations are computed within 13 modules, each existing as a

separate worksheet within the main Excel spreadsheet. Each module tracks changes over a 10-year period for its respective variables. Within these inter-connected modules (Figure 5), the impact of inputs, random variables, and technology-induced improvements are estimated over time using the underlying system behavior within the model. Results of calculations within one module often affect calculations in other modules with multiple feed-forward and feed-backward interdependencies. Each of these modules eventually results in a calculation that will influence the cost and revenue flows necessary for the partial budget analysis. Finally, the costs and revenues are utilized for the project analysis examining the net present value (NPV) and financial feasibility of the project along with associated sensitivity analyses.

Agricultural commodity markets are characterized by tremendous volatility, and in many countries, this volatility is increasing with reduced governmental price regulation. As a result, economic conditions and the profitability of investments can vary considerably, depending on the prices paid for inputs and the prices received for outputs. Producers are often critical of economic analyses that fail to account for this volatility by using a single value for critical prices, recognizing that the results of the analysis may be different with higher or lower milk prices, for example. In a simulation model, variability in prices can be accounted for by considering the random variation of these variables. In this model, historical U.S. prices from 1971 to 2006 for milk, replacement heifers, alfalfa, corn, and soybeans were collected from the “Understanding Dairy Markets” website (Gould, 2007). Historical cull cow prices were defined using the USDA-National Agricultural Statistics Service values for “beef cows and cull dairy cows sold for slaughter” (USDA-NASS, 2007). Base values for future prices (2007 to 2016) of milk, corn, soybeans, alfalfa, and cull cows were set using estimates from the Food and Agricultural Policy Research Institute’s (FAPRI) U.S. and World Agricultural Outlook Report (FAPRI, 2007).

Variation in prices was considered within the simulation based on historical variation. In this manner, the volatility in key prices can be considered within a profitability analysis.

Although there is probably no direct way to account for the many decisions that ultimately impact the actual profitability of an investment in a Precision Dairy Farming technology, this model includes a Best Management Practice Adherence Factor (**BMPAF**) to represent the potential for observing the maximum benefits from adopting a technology. The BMPAF is a crude scale from 1 to 100% designed, to represent the level of the farm management. At a value of 100%, the assumption is that the farm management is capable and likely to utilize the technology to its full potential. Consequently, they would observe the maximum benefit from the technology. On the other end of the spectrum, a value of 0% represents a scenario where farm management installs a technology without changing management to integrate the newly available data in efforts to improve herd performance. In this case, the farm would not recognize any of the benefits of the technology. Perhaps most importantly, sensitivity analyses allow the end user to evaluate the decision with knowledge of the role they play in its success.

Investment analysis of automated body condition scoring

The model was used for an investment analysis of the proposed system for automatically monitoring BCS on dairy farms. The primary objective of this effort was to identify the factors that influence the potential profitability of investing in an automated BCS system. An expert opinion survey was conducted to provide estimates for potential improvements associated with technology adoption. Benefits of technology adoption were estimated through assessment of the impact of BCS on the incidence of ketosis, milk fever, metritis, conception rate at first service, and energy efficiency.

For this research example, industry averages for production and financial parameters, selected to represent conditions for a U.S. dairy farm milking 1000 cows in 2007 were used.

The NPV was the metric used to assess the profitability of the investment. The default discount rate of 8% was adjusted to 10% because this technology has not been marketed commercially, thus the risk for early adopters of the technology is higher. The discount rate partially accounts for this increased risk by requiring higher returns from the investment. The general rule of thumb is that a decision with a NPV greater than 0 is a “go” decision and a worthwhile investment for the business. The investment at the beginning of the project includes the purchase costs of the equipment needed to run the system in addition to purchasing any other setup costs or purchases required to start the system. Recognizing that a simpler model ignores the uncertainty inherent in a dairy system, Monte Carlo simulation was conducted using the @Risk add-in. This type of simulation provides infinite opportunities for sensitivity analyses. Simulations were run using 1000 iterations in each simulation. Simulations were run using estimates provided by experts for scenarios with little to no improvement in the distribution of BCS and with definite improvement.

Results and Discussion

Digital imaging

Because of problems with lighting or setup limitations with the experimental equipment, usable images were available only for 46 of 61 possible days. The average number of usable images per day was 72.44 with a SD of 42.91 and a range of 6 to 149. Usable images were available for 242 different cows. On average, there were 13.77 images per cow with a SD of 8.59 and a range of 1 to 38. The primary reason for deeming an image as non-usable was lighting because there was simply not enough contrast between the background and

the cow’s body to identify anatomical landmarks. This issue was more prominent for cows that were predominantly black; predominantly white cows were much easier to identify. There were also issues with regard to cow position beneath the camera. In some cases, an image was taken of either the front or rear quarter of the cow, preventing assessment of the anatomical points of interest. Cows standing at an angle within the weigh station were also a problem. Tails moving within images and dirt also prevented some images from being used.

Correlations were calculated between USBCS and UKBCS and weekly composite angles. All correlations of composite angles with USBCS were significantly different from zero ($P < 0.01$). Correlations with UKBCS were significantly different from zero ($P < 0.02$) for all composite angles except tail angle. The hook posterior angle ($r = 0.5239$), hook angle ($r = 0.4834$), and tailhead depression ($r = 0.3104$) had the strongest correlations with USBCS. The hook posterior angle ($r = 0.4601$), hook angle ($r = 0.3301$), hook anterior curvature ($r = 0.1984$), and tailhead depression ($r = 0.1856$) had the strongest correlations with UKBCS. Although the correlations of USBCS and UKBCS with the hook anterior angle were moderate ($r = 0.2459$ and 0.1416 , respectively), they were not nearly as strong as with hook posterior angle. This demonstrates that the cow is more likely to deposit fat in the area between the hooks and thurls than around the short ribs.

For each angle, a trend of increasing angle size with increasing BCS was observed for both systems. In other words, as BCS increases, the angle flattens toward a straight line (180°). For hook angle and hook posterior angle, this indicates that the hooks are less sharp or prominent with increasing BCS. In fact, this is similar to the descriptions that Ferguson et al. (1994) use within their flowchart distinguishing between round or angular hooks. For

the tailhead depression, this indicates that the angle reflecting the depression around the tailhead changes as this region fills with body reserves. This corresponds to the use of the coccygeal (tailhead) ligament within the Ferguson et al. (1994) flowchart. Another way of describing these changes is that the degree of “boniness” changes as the level of fat varies (Coffey et al., 2003). These results support our hypothesis that BCS is reflected in angles around the hooks and rump as measured using digital images.

The primary objective of this work was to develop models to describe BCS using this information obtained from the collected digital images. For the USBCS model, 100% of predicted BCS were within 0.50 points of actual BCS and 92.79% were within 0.25 points. For the UKBCS model, 99.87% of predicted BCS were within 0.50 points of actual BCS and 89.95% were within 0.25 points. These results were similar to those of Leroy et al. (2005) who found, on a series of 32 test images, the deviation between the calculated score and a BCS assessed by an expert was 0.27. In lactating buffalo, Negretti et al. (2008) reported differences of 0.21, 0.26, and 0.27 units between subjectively evaluated BCS using a 1 to 9 scale and calculated BCS using 3 different equations. However, the range of scores of animals in this study was fairly narrow (5 to 8). Ferguson et al. (1994) found that human observers agreed with a modal BCS of 4 observers 58.1% of the time and varied by only 0.25 units 32.6% of the time. Thus, BCS changes of 0.25 cannot realistically be detected, even with trained observers. In our data set, the agreement between subjective BCS and BCS as predicted by image analysis was similar to the expected difference between 2 different subjective BCS observers.

Examples of images from a thin and a fat cow (Figure 6) demonstrate visually the difference in the contours of animals of varying BCS. The thin cow’s hooks are much more prominent and pronounced than those of the fat cow, and this is

reflected in the difference in the angles measured from these images. Further, the depression around the tailhead is more pronounced. Predicted scores from these models against actual scores for both systems are depicted in Figure 7. In models predicting both USBCS and UKBCS, the residuals increase in magnitude with increasing BCS. In effect, these models over-predict the BCS of thin cows and under-predict the BCS of fat cows. This result should not be surprising given that in a well-managed herd, such as the one used in this study, few cows score at either extreme of the BCS scale. Thus, this result is likely reflective of inadequate data from cows with particularly low or high BCS to properly predict their BCS using images.

Future efforts in this area should strive to work in large herds where, even in a normal distribution, more cows in extreme categories will exist or in herds with an unusual number of thin and fat cows. The ability to identify thin and fat cows is imperative for successful on-farm adoption of automated BCS as this is where the real value of BCS lies. The largest benefits in body condition scoring result from using information about why cows are outside of the optimal BCS range for their respective parity and stage of lactation to improve herd nutritional management strategies.

Limitations and future considerations

If images were consistently available on a daily basis for all cows, models could be improved through the use of more stringent outlier removal strategies. With 7 images in a week, an image with angles that clearly deviated from the other images during that week could be removed prior to assignment of a predicted BCS. Unfortunately, using such strict rules in this small data set would have removed too many images, resulting in only a small pool of images for model development. Future research efforts should focus on ways of obtaining images more frequently using a larger number of animals across a wider range of scores to improve

upon the relationships demonstrated here. Because of the short duration of this project, we were unable to determine if the measured angles changed within cows, reflecting the changes expected in a cow's BCS during a lactation. Before technology adoption, it is essential to establish that this important pattern is reflected using images from cows followed through complete lactations.

Another limitation to consider is potential error in identifying the anatomical points of interest. The human eye and hand are subject to some degree of error. Furthermore, the anatomical points chosen do not necessarily all correspond to an obvious visual clue. Similarly, the USBCS were provided by one evaluator and the UKBCS by 2 evaluators. Consequently, subjectivity and human error limit the value of collected BCS as predictors in the developed models.

An automated method of point extraction may prove superior to this manual extraction technique. While previous work has focused primarily on images of the rear of the cow (Coffey, 2003; Leroy et al., 2005, Pompe et al., 2005), this research focused on a top-down view of the cow. To gain a better perspective of the cow's anatomy, it may be necessary to combine these 2 approaches, possibly aiming for a 3-dimensional view of the animal.

In the models presented here, the number of angles (2 to 3) used in prediction equations is relatively limited. Edmonson et al. (1989) stated that a score from a single area is a good indication of overall BCS. However, observational BCS involves assimilation of information about multiple visual cues of the cow by the human brain. Whether 2 to 3 points will provide a sufficient representation of overall energy reserves remains to be determined. Perhaps, more accurate algorithms could be developed, compiling information from additional geometrical calculations. Although not possible with the images in this data set, it would be beneficial if

adjustment could be made for differences in cow size and posture (Leroy et al., 2005).

While the results of this study demonstrate a clear relationship between angles calculated using digital images and BCS, this relationship may or may not imply a relationship with actual body fat content. Estimates as to the degree with which BCS represents actual body fat have varied considerably with correlation coefficients of 0.57 to 0.90 (Wright and Russel, 1984; Otto et al., 1991; Waltner et al., 1994). Although BCS is used as the "gold standard" for assessing body energy reserves, it is not a perfect measure of energy reserves and is limited by its subjectivity. Future efforts should attempt to define how BCS obtained from image analysis reflects actual body fat in addition to subjective BCS. Initially, this may be accomplished using a more objective measurement of energy reserves, such as ultrasound. However, with a goal of determining the amount of fat within an animal's body, the highest degree of accuracy can be obtained only in a post-slaughter chemical analysis of the entire body with contents of the digestive and urinary tracts removed (Otto, 1990). It may also be useful to measure the angles around the hooks and pins used in this study on live animals to compare with angles calculated using image analysis.

Profitability analysis

In a simulation with a small likelihood of improvement in BCS distribution, 12.6% of simulation iterations resulted in a positive NPV, whereas this same number was 86.6% for the scenario with a definite improvement in BCS distribution. In other words, using the model assumptions for an average 1000-cow U.S. dairy in 2007, investing in an automated BCS system was the right decision 12.6 or 86.6% of the time, depending on the assumption of what would happen with BCS distribution after technology adoption. The individual decision maker's level of risk aversion would then determine whether they should make

the investment. Although this serves as an example of how this model could be used for an individual decision maker, this profitability analysis should not be taken literally. In reality, an individual dairy producer would need to look at this decision using herd-specific variables to assess the investment potential of the technology. The main take home message from these simulations was that because results from the investment analysis were highly variable, this technology is certainly not a “one size fits all” technology that would prove beneficial for all dairy producers.

Sensitivity analyses

The primary objective of this research was to gain a better understanding of the factors that would influence the profitability of investing in an automated BCS system through sensitivity analysis. Sensitivity analysis, designed to evaluate the range of potential responses, provides further insight into an investment analysis (van Asseldonk et al., 1999). In sensitivity analyses, tornado diagrams visually portray the effect of either inputs or random variables on an output of interest. In a tornado diagram, the lengths of the bars are representative of the sensitivity of the output to each input. The tornado diagram is arranged with the most sensitive input at the top, progressing toward the least sensitive input at the bottom. In this manner, it is easy to visualize and compare the relative importance of inputs to the final results of the model. Improvements in reproductive performance had the largest influence on revenues, followed by energy efficiency and then by disease reduction. Random variables that had the most influence on NPV were as follows: variable cost increases after technology adoption; the odds ratios for ketosis and milk fever incidence and conception rates at first service associated with varying BCS ranges; uncertainty of the impact of ketosis, milk fever, and metritis on days open, unrealized milk, veterinary costs, labor, and discarded milk; and the change in the percent of cows with BCS at calving $d^{>3.25}$ before and after

technology adoption. Scatter plots of the most sensitive random variables plotted against NPV, along with correlation coefficients, demonstrate how random variables impact profitability. In both simulations, the random variable that had the strongest relationship with NPV was the variable cost increase. Not surprisingly, as the variable costs per cow increased; the NPV decreased in both simulations (Figure 8). Thus, the value of an automated BCS system was highly dependent on the costs incurred to utilize the information provided by the system to alter nutritional management for improved BCS profiles.

Finally, the results of any simulation model are highly dependent on the assumptions within the model. A one-way sensitivity analysis tornado diagram compares multiple variables on the same graph. Essentially, each input is varied (1 at a time) between feasible high and low values, and the model is evaluated for the output at those levels, holding all other inputs at their default levels. On the tornado diagram, for each input, the lower value is plotted at the left end of the bar and the higher value at the right end of the bar (Clemen, 1996). Simulations were run for high and low feasible values for 6 key inputs that may affect NPV. The tornado diagram for the 95th percentile NPV from the simulation with a small likelihood of improvement in BCS distribution is presented in Figure 9. Herd size had the most influence on NPV. The NPV was higher for the larger herd because the investment costs and benefits were spread among more cows.

The next most important variable was the BMPAF. Again, this result was not surprising and reiterates that one of the most important determinants of project success was what the producer actually does to manage the information provided by the technology. There are many nutritional, health, reproductive, and environmental decisions made by the dairy producer that have a major impact on changes in body reserves for both individual cows and groups of cows. Management

level plays a critical role in determining returns from investing in a Precision Dairy Farming technology. The level of management in day-to-day handling of individual cows may also influence the impact of Precision Dairy Farming technologies. Van Asseldonk (1999) defined management capacity as “having the appropriate personal characteristics and skills to deal with the right problems and opportunities in the right moment and in the right way.” Effective use of an information system requires an investment in human capital in addition to investment in the technology (Streeter and Hornbaker, 1993). Then, the level of milk production was the next most sensitive input. As the level of milk production increased, the benefits of reducing disease incidence and calving intervals increased. As would be expected, the NPV increased with an increased base incidence of ketosis because the effects of BCS on ketosis would be exaggerated. The purchase price of the technology had a relatively small impact on the NPV, as did the base culling rate.

Conclusion

The potential applications for automated body condition scoring are immense. This research builds upon the work of Coffey (2003), demonstrating the potential for the use of digital images in assessing BCS of dairy cattle. In our work, there appears to be a strong relationship between the angles measured and BCS as determined by trained evaluators. Clearly, the manual identification of points is not feasible beyond labor-intensive research studies. Although the tailhead information did not add much value to predictive models in this study, the potential for using this information to supplement hook descriptions should be explored further in future work. Finally, future studies should place strong emphasis on selecting herds with ample numbers of cows with low and high BCS to ensure that automated scoring systems accurately detect these critically important animals.

Because of limitations related to lighting and separation of the cow image from the background of the image, standard digital photography may not function well in an automated system. Rather, other technologies, such as thermal imaging, should be explored to facilitate automatic extraction of information from images. Arias et al. (2004) successfully demonstrated how digital image processing and neural networks could be used for automatic extraction of morphological descriptions of a cow’s body using differences in color within an image. As these imaging technologies are applied to other industries, costs of these technologies will continue to decrease. Similarly, computer storage limitations are no longer a major concern. Once the aforementioned technical difficulties are overcome, automated BCS may become an integral part of decision making on modern dairy farms.

Precision Dairy Farming technologies provide tremendous opportunities for improvements in individual animal management on dairy farms. Formal investment analyses can help producers in deciding which technologies should be purchased. Dairy producers and consultants are accustomed to seeing results from more simple economic analyses that present investment decisions as “black and white” or “good or bad” scenarios. In reality, very few economic decisions for dairy farms are that clear-cut. Examining decisions with a simulation model accounts for more of the risk and uncertainty characteristic of the dairy system. Given this risk and uncertainty, a random investment analysis will represent that there is uncertainty in the profitability of some projects. Ultimately, the dairy manager’s level of risk aversion will determine whether or not he or she invests in a technology using the results from this type of analysis. Perhaps the most interesting conclusion from this research was that the factors that had the most influence on the profitability investment in an automated BCS system were those related to what happens with the technology after it has been purchased, as indicated by the increase in variable costs needed for

management changes and the management capacity of the farm. Decision support tools, such as this one, that are designed to investigate dairy herd decisions at a systems level may help dairy producers make better decisions.

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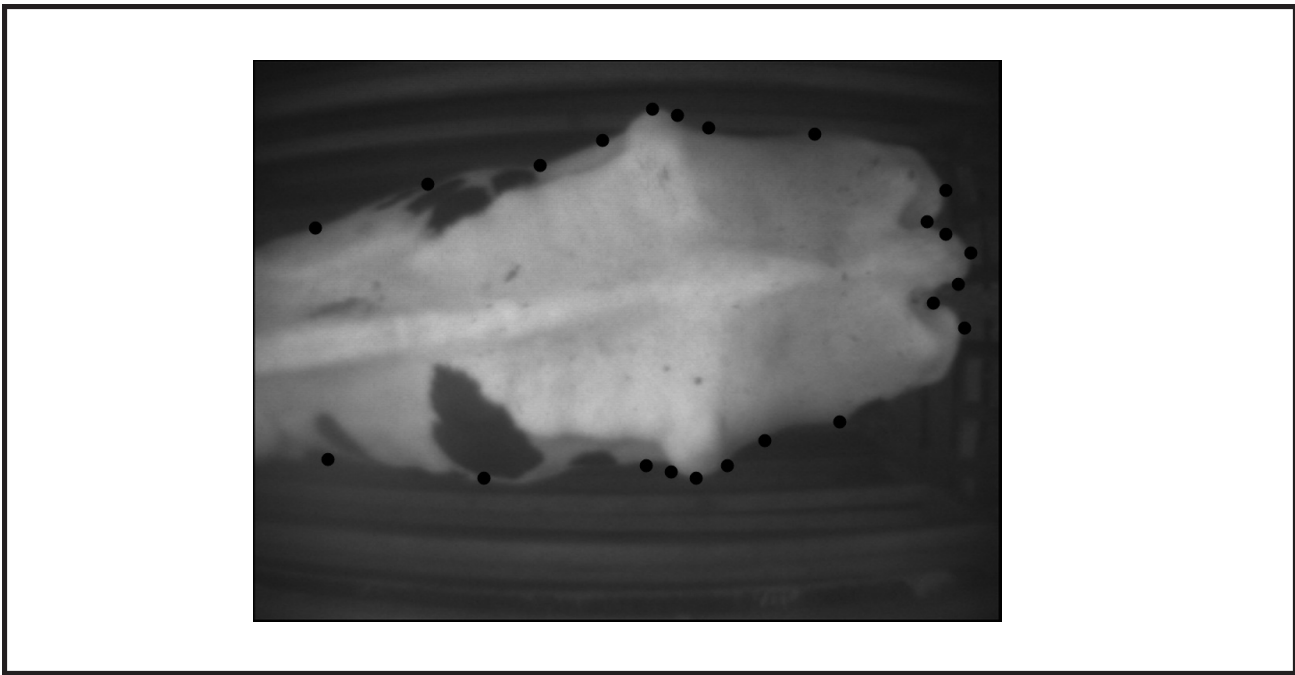


Figure 1. Twenty-three key anatomical points identified (where possible) for each image (Bewley et al., 2008).

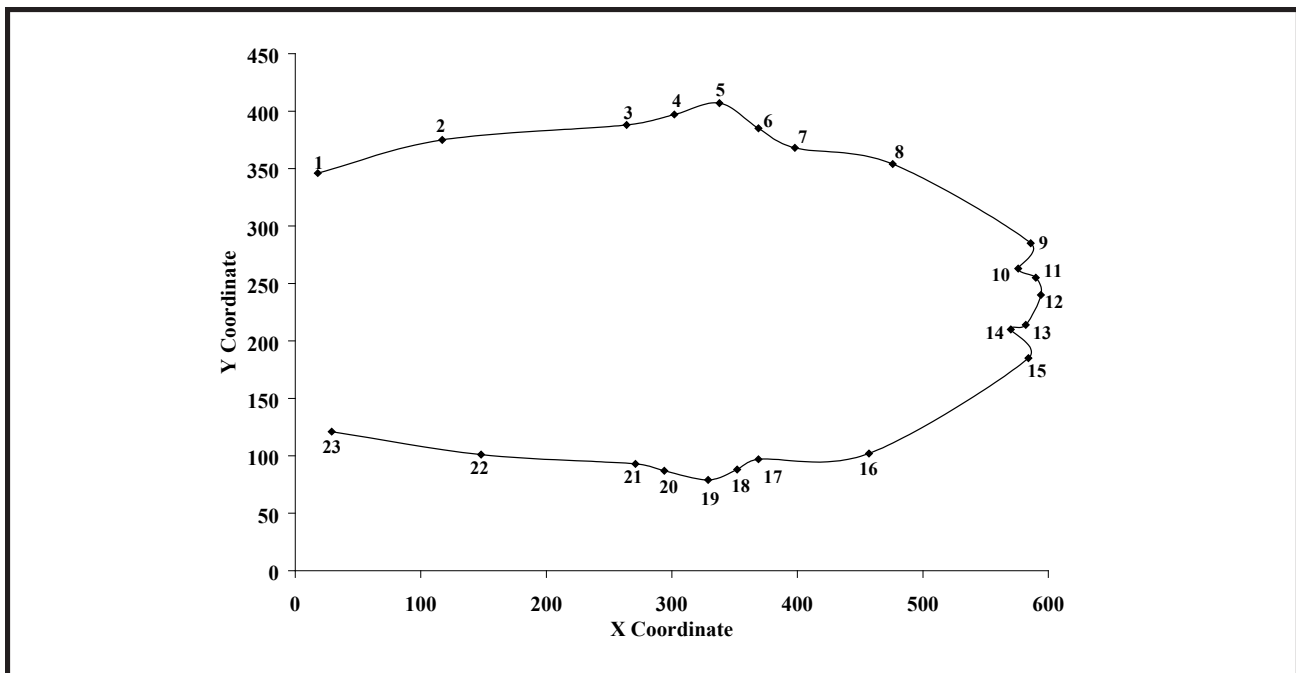


Figure 2. Sample cow outline using 23 key anatomical points [(1) Left Forerib, (2) Left Short Rib Start, (3) Left Hook Start, (4) Left Hook Anterior Midpoint, (5) Left Hook, (6) Left Hook Posterior Midpoint, (7) Left Hook End, (8) Left Thurl, (9) Left Pin, (10) Left Tailhead Nadir, (11) Left Tailhead Junction, (12) Tail, (13) Right Tailhead Junction, (14) Right Tailhead Nadir, (15) Right Pin, (16) Right Thurl, (17) Right Hook End, (18) Right Hook Posterior Midpoint, (19) Right Hook, (20) Right Hook Anterior Midpoint, (21) Right Hook Start, (22) Right Short Rib Start, and (23) Right Forerib] (Bewley et al., 2008).

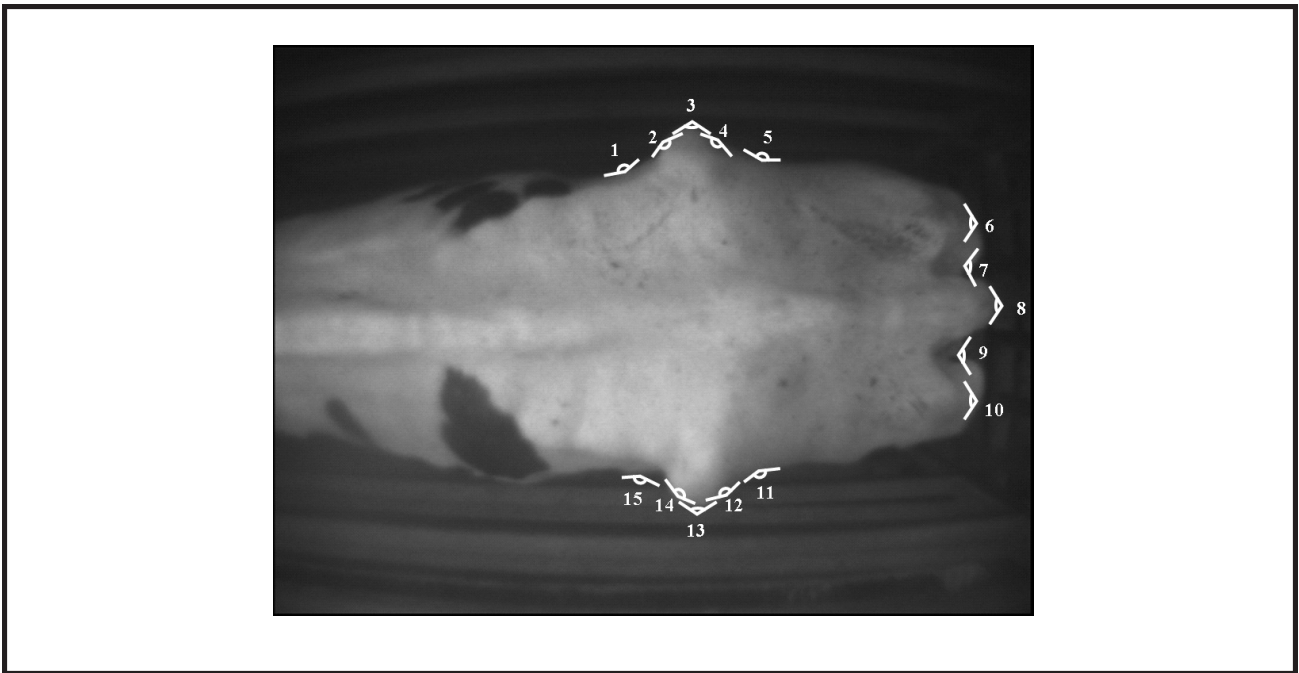


Figure 3. Angles calculated using the key anatomical points: [(1) Left Hook Anterior Angle, (2) Left Hook Anterior Curvature, (3) Left Hook Angle, (4) Left Hook Posterior Angle, (5) Left Hook Posterior Curvature, (6) Left, Thurl to Pin Angle, (7) Left Tailhead Depression, (8) Tailhead Angle, (9) Right Tailhead Depression, (10) Right Thurl to Pin Angle, (11) Right Hook Posterior Angle, (12) Right Hook Posterior Curvature, (13) Right Hook Angle, (14) Right Hook Anterior Curvature, and (15) Right Hook Anterior Angle] (Bewley et al., 2008).

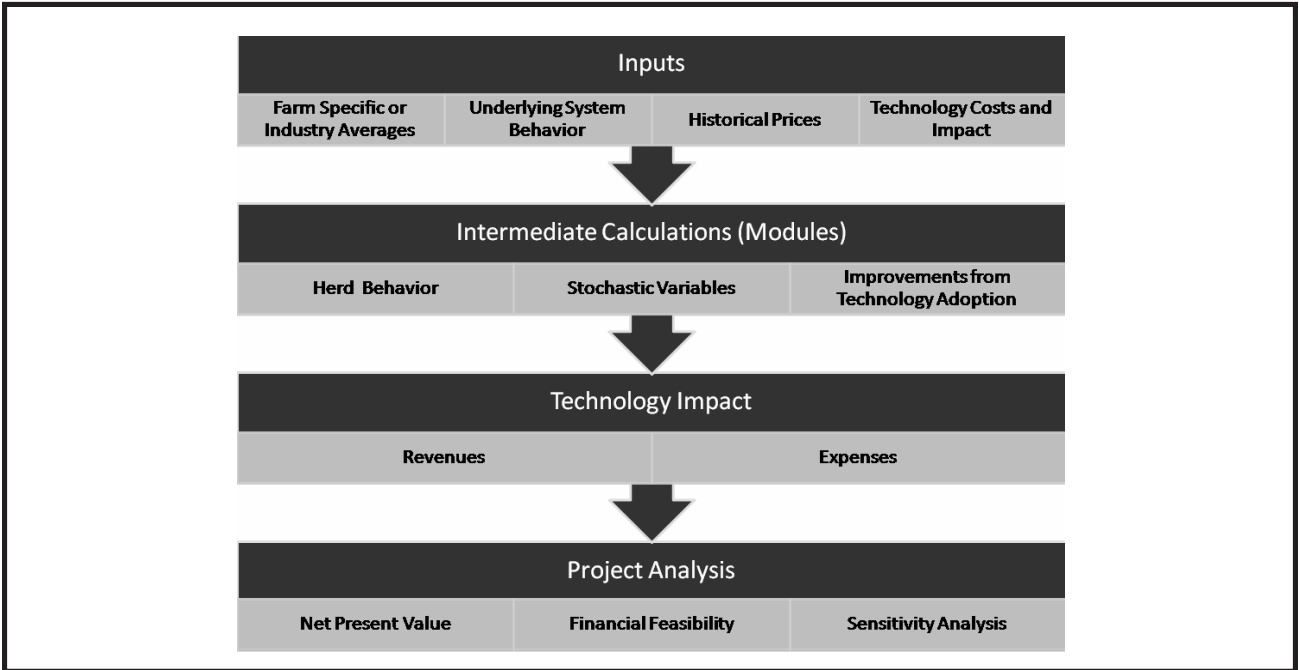


Figure 4. Diagram depicting general flow of information within the Precision Dairy Farming investment model.

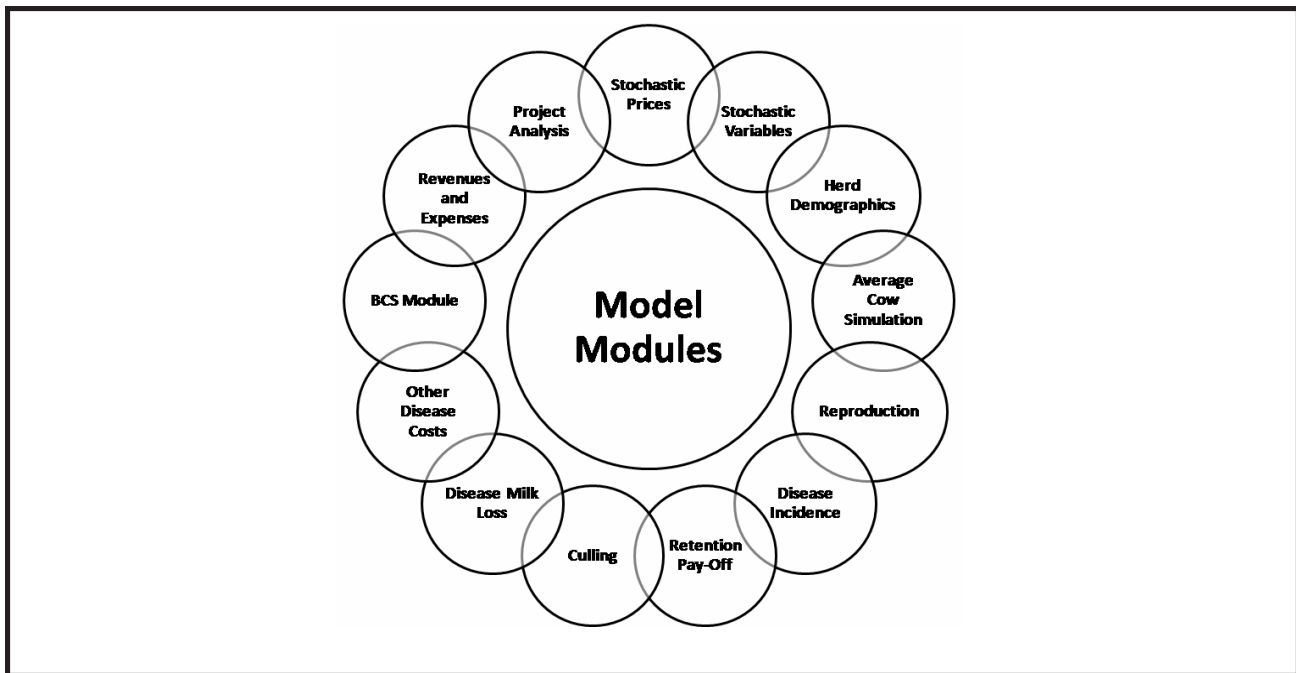


Figure 5. Diagram of Precision Dairy Farming investment model modules.

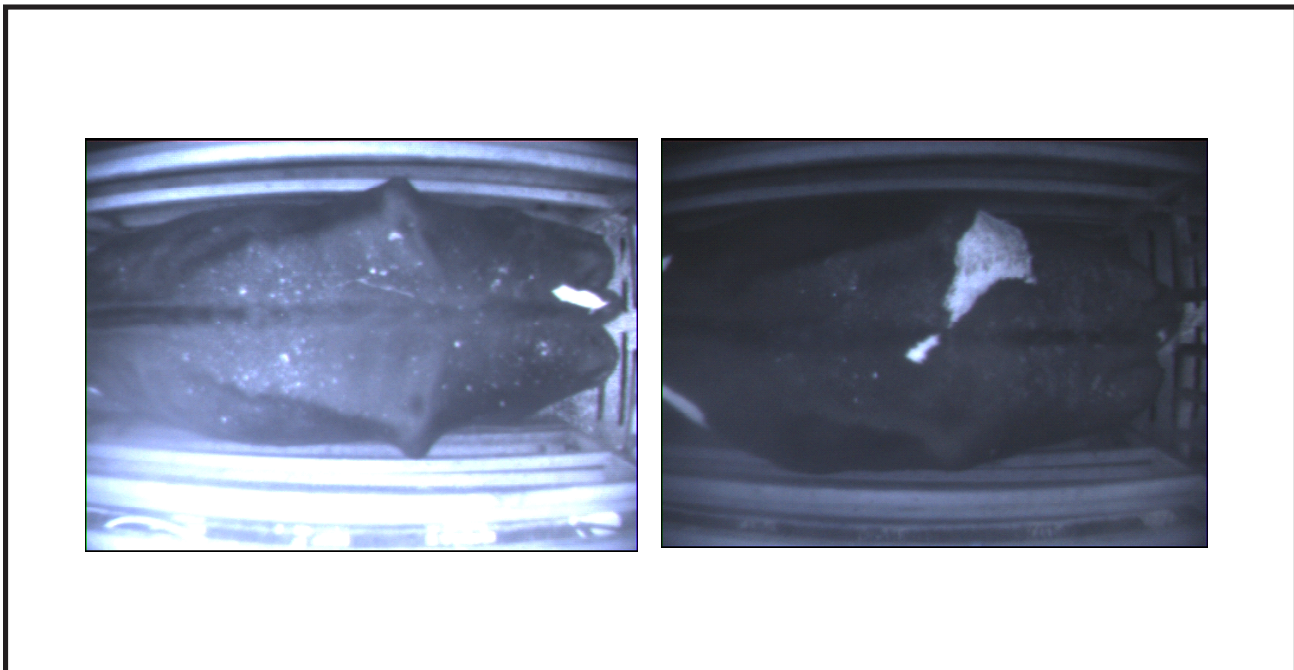


Figure 6. Examples of predicted USBCS of a thin¹ and fat² cow (Bewley et al., 2008).

¹ (Left) USBCS = 2.50, Predicted USBCS = 2.63, Average Posterior Hook Angle = 149.99°, and Average Hook Angle = 116.62°

² (Right) USBCS = 3.50, Predicted USBCS = 3.62, Average Posterior Hook Angle = 172.14°, and Average Hook Angle = 153.47°.

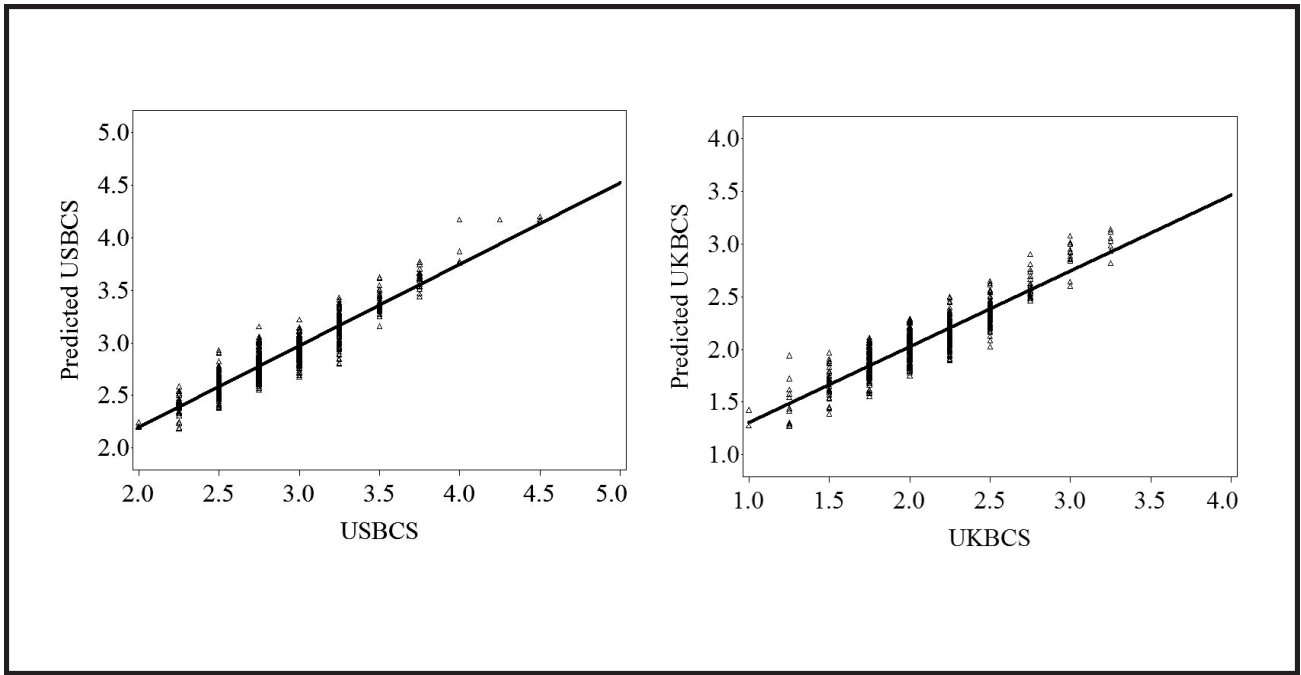


Figure 7. Predicted versus actual USBCS and UKBCS (Bewley et al., 2008).

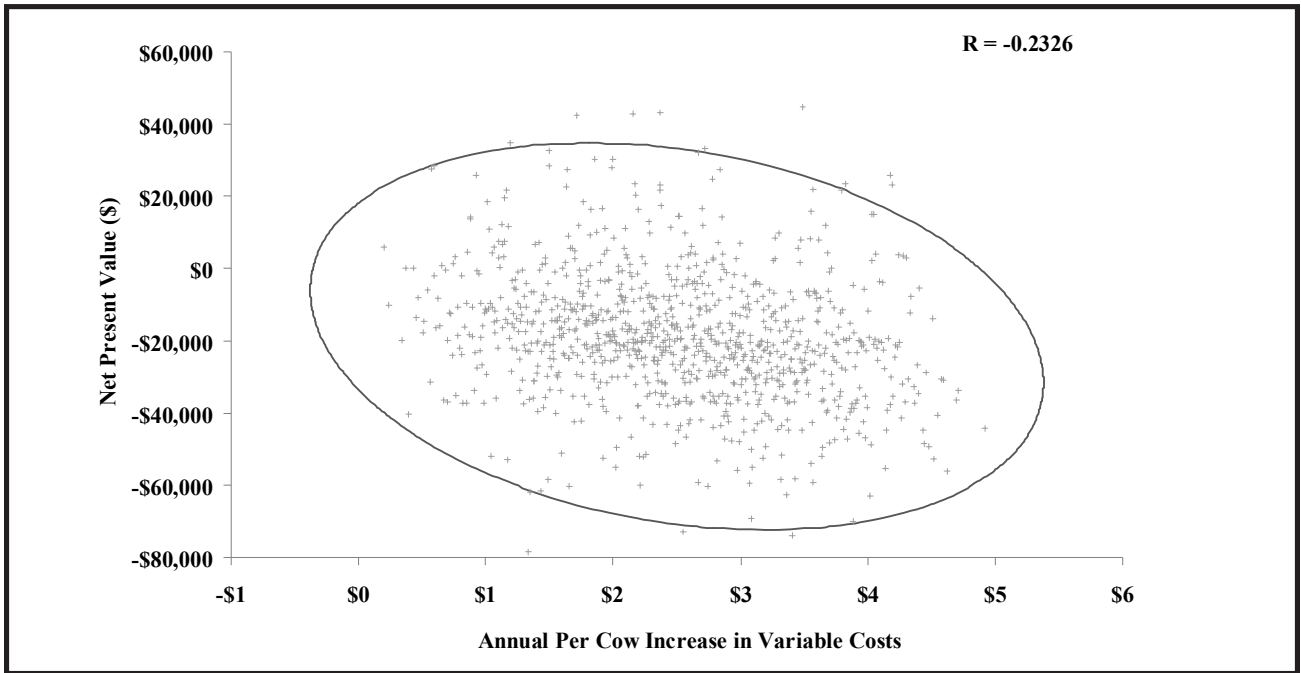


Figure 8. Scatter plot of Net Present Value versus annual percentage increase in variable costs (for simulation using all expert opinions provided).

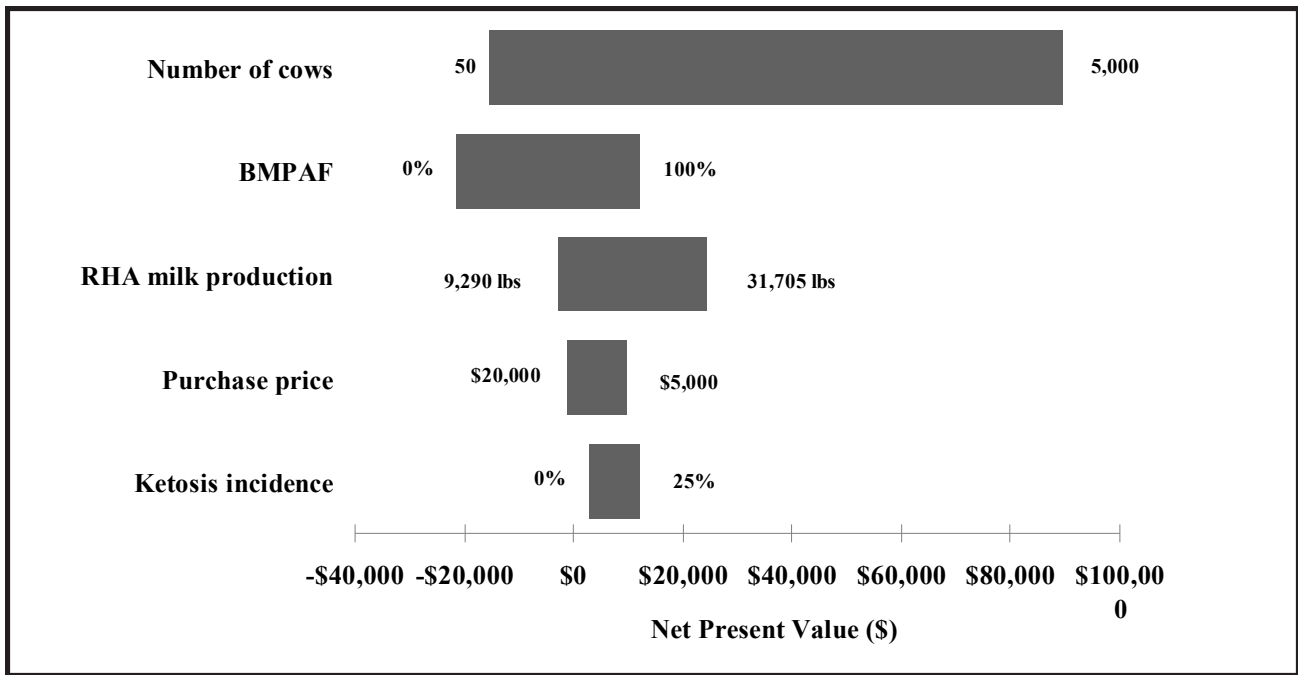


Figure 9. Tornado diagrams for inputs affecting 95th percentile of Net Present Value for simulations using the estimates of all survey respondents¹.

¹BMPAF = Best Management Practice Adherence Factor and RHA milk production rolling herd average milk production (lb).