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Élevage laitier de précision : défis et opportunités

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Élevage laitier de précision : défis et opportunités

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- Precision Dairy Farming is the use of technologies to measure physiological, behavioral, and production indicators on individual animals to improve management strategies and farm performance.
- Many Precision Dairy Farming technologies, including daily milk yield recording, milk component monitoring, pedometers, automatic temperature recording devices, milk conductivity indicators, automatic estrus detection monitors, and daily body weight measurements, are already being utilized by dairy producers.
- Other theoretical Precision Dairy Farming technologies have been proposed to measure jaw movements, ruminal pH, reticular contractions, heart rate, animal positioning and activity, vaginal mucus electrical resistance, feeding behavior, lying behavior, odor, glucose, acoustics, progesterone, individual milk components, color (as an indicator of cleanliness), infrared udder surface temperatures, and respiration rates.
- The main objectives of Precision Dairy Farming are maximizing individual animal potential, early detection of disease, and minimizing the use of medication through preventive health measures.
- Perceived benefits of Precision Dairy Farming technologies include increased efficiency, reduced costs, improved product quality, minimized adverse environmental impacts, and improved animal health and well-being.
- Real time data used for monitoring animals may be incorporated into decision support systems designed to facilitate decision making for issues that require compilation of multiple sources of data.
- Technologies for physiological monitoring of dairy cows have great potential to supplement the observational activities of skilled herdspersons, which is especially critical as more cows are managed by fewer skilled workers.
- The economic implications of technology adoption must be explored further to increase adoption rates of Precision Dairy Farming technologies.

INTRODUCTION

Across the globe, the trend toward fewer, larger dairy operations continues. Dairy operations today are characterized by narrower profit margins than in the past, largely because of reduced governmental involvement in regulating agricultural commodity prices. Consequently, small changes in production or efficiency can have a major impact on profitability. The resulting competition growth has intensified the drive for efficiency resulting in increased emphasis on business and financial management. Furthermore, the decision making landscape for a dairy manager has changed dramatically with increased emphasis on consumer protection, continuous quality assurance, natural foods, pathogen-free food, zoonotic disease transmission, reduction of the use of medical treatments, and increased concern for the care of animals. These changing demographics reflect a continuing change in the way in which dairy operations are managed. In large part, many of these changes can be attributed to tremendous technological progress in all facets of dairy farming, including genetics, nutrition, reproduction, disease control, and management. W. Nelson Philpot (2003) captured this change effectively in describing modern dairy farms as “technological marvels”. Conceivably, the next “technological marvel ” in the dairy industry may be in Precision Dairy Farming.

What is Precision Dairy Farming?

Precision Dairy Farming is the use of technologies to measure physiological, behavioral, and production indicators on individual animals to improve management strategies and farm performance. Many Precision Dairy Farming technologies, including daily milk yield recording, milk component monitoring (e.g. fat, protein, and SCC), pedometers, automatic temperature recording devices, milk conductivity indicators, automatic estrus detection monitors, and daily body weight measurements, are already being utilized by dairy producers. Eastwood et al. (2004) defined Precision Dairy Farming as "the use of information technologies for assessment of fine-scale animal and physical resource variability aimed at improved management strategies for optimizing economic, social, and environmental farm performance." Spilke and Fahr (2003) stated that Precision Dairy Farming, with specific emphasis on technologies for individual animal monitoring, "aims for an ecologically and economically sustainable production of milk with secured quality, as well as a high degree of consumer and animal protection". With Precision Dairy Farming, the trend toward group management may be reversed with focus returning to individual cows through the use of technologies (Schulze et al., 2007). Technologies included within Precision Dairy Farming range in complexity from daily milk yield recording to measurement of specific attributes (e.g. fat content or progesterone) within milk at each milking. The main objectives of Precision Dairy Farming are maximizing individual animal potential, early detection of disease, and minimizing the use of medication through preventive health measures. Precision Dairy Farming is inherently an interdisciplinary field incorporating concepts of informatics, biostatistics, ethology, economics, animal breeding, animal husbandry, animal nutrition, and engineering (Spilke and Fahr, 2003).

Potential Benefits of Precision Dairy Farming

Perceived benefits of Precision Dairy Farming technologies include increased efficiency, reduced costs, improved product quality, minimized adverse environmental impacts, and improved animal health and well-being. These technologies are likely to have the greatest impact in the areas of health, reproduction, and quality control (de Mol, 2000). Realized benefits from data summarization and exception reporting are anticipated to be higher for larger herds, where individual animal observation is more challenging and less likely to occur (Lazarus et al., 1990). As dairy operations continue to increase in size, Precision Dairy Farming technologies become more feasible because of increased reliance on less skilled labor and the ability to take advantage of economies of size related to technology adoption.

A Precision Dairy Farming technology allows dairy producers to make more timely and informed decisions, resulting in better productivity and profitability (van Asseldonk et al., 1999b). Real time data can be used for monitoring animals and creating exception reports to identify meaningful deviations. In many cases, dairy management and control activities can be automated (Delorenzo and Thomas, 1996). Alternatively, output from the system may provide a recommendation for the manager to interpret (Pietersma et al., 1998). Information obtained from Precision Dairy Farming technologies is only useful if it is interpreted and utilized effectively in decision making. Integrated, computerized information systems are essential for interpreting the mass quantities of data obtained from Precision Dairy Farming technologies. This information may be incorporated into decision support systems designed to facilitate decision making for issues that require compilation of multiple sources of data.

Historically, dairy producers have used experience and judgment to identify outlying animals. While this skill is invaluable and can never be fully replaced with automated technologies, it is inherently flawed by limitations of human perception of a cow's condition. Often, by the time an animal exhibits clinical signs of stress or illness, it is too late to intervene. These easily observable clinical symptoms are typically preceded by physiological responses evasive to the human eye (e.g. changes in temperature or heart rate). Thus, by identifying changes in physiological parameters, a dairy manager may be able to intervene sooner. Technologies for physiological monitoring of dairy cows have great potential to supplement the observational activities of skilled herdspersons, which is especially critical as more cows are managed by fewer skilled workers (Hamrita et al., 1997).

Precision Dairy Farming Examples

The list of Precision Dairy Farming technologies used for animal status monitoring and management continues to grow. Because of rapid development of new technologies and supporting applications, Precision Dairy Farming technologies are becoming more feasible. Many Precision Dairy Farming technologies including daily milk yield recording, milk component monitoring (e.g. fat, protein, and SCC), pedometers, automatic temperature recording devices, milk conductivity indicators, automatic estrus detection monitors, and daily body weight measurements are already being utilized by dairy producers. Despite its seemingly simplistic nature, the power of accurate milk weights should not be discounted in monitoring cows, as it is typically the first factor that changes when a problem develops (Philpot, 2003). Other theoretical Precision Dairy Farming technologies have been proposed to measure jaw movements, ruminal pH, reticular contractions, heart rate, animal positioning and activity, vaginal mucus electrical resistance, feeding behavior, lying behavior, odor, glucose, acoustics, progesterone, individual milk components, color (as an indicator of cleanliness), infrared udder surface temperatures, and respiration rates. Unfortunately, the development of technologies tends to be driven by availability of a technology, transferred from other industries in market expansion efforts, rather than by need. Relative to some industries, the dairy industry is relatively small, limiting corporate willingness to invest extensively in development of technologies exclusive to dairy farms. Many Precision Dairy Farming technologies measure variables that could be measured manually, while others measure variables that could not have been obtained previously.

A Validation Example

The objective of a recent study (Borhers et al, 2016) was to evaluate commercially available precision dairy technologies against direct visual observations of feeding, rumination, and lying behaviors. Primiparous (n = 24) and multiparous (n = 24) lactating Holstein dairy cattle (mean ± SD; 223.4 ± 117.8 days in milk, producing 29.2 ± 8.2 kg milk/d) were fitted with 6 different triaxial accelerometer technologies evaluating cow behaviors at or before freshening. The AfiAct Pedometer Plus (Afimilk, Kibbutz Afikim, Israel) was used to monitor lying time. The CowManager SensOor (Agis, Harmelen, Netherlands) monitored rumination and feeding time. The HOBO Data Logger (HOBO Pendant G Acceleration Data Logger, Onset Computer Corporation, Pocasset, MA) monitored lying time. The CowAlert IceQube (IceRobotics Ltd, Edinburgh, Scotland) monitored lying time. The Smartbow (Smartbow GmbH, Jutogasse, Austria) monitored rumination time. The Track A Cow (ENGS, Rosh Pina, Israel) monitored lying time and time spent around feeding areas for the calculation of feeding time. Over 8 days, 6 cows per day were visually observed for feeding, rumination, and lying behaviors for 2 h after morning and evening milking. The time of day was recorded when each behavior began and ended. These times were used to generate the length of time behaviors were visually observed. Pearson correlations (calculated using the CORR procedure of SAS Version 9.3, SAS Institute Inc., Cary, NC), and concordance correlations (CCC; calculated using the epiR package of R version 3.1.0, R Foundation for Statistical Computing, Vienna, Austria) evaluated association between visual observations and technology-recorded behaviors. Visually recorded feeding behaviors were moderately correlated with the CowManager SensOor (r = 0.88, CCC = 0.82) and Track A Cow (r = 0.93, CCC = 0.79) monitors. Visually recorded rumination behaviors were strongly correlated with the Smartbow (r = 0.97, CCC = 0.96), and minorly correlated with the CowManager SensOor (r = 0.69, CCC = 0.59). Visually recorded lying behaviors were strongly correlated with the AfiAct Pedometer Plus (r > 0.99, CCC > 0.99), CowAlert IceQube (r > 0.99, CCC > 0.99), and Track A Cow (r > 0.99, CCC > 0.99). HOBO Data Loggers were moderately correlated (r > 0.83, CCC > 0.81) with visual observations. Based on these results, the evaluated precision dairy monitoring technologies accurately monitored dairy cattle behavior.

Investment Analysis of Precision Dairy Farming Technologies

Today's dairy manager is presented with a constant stream of new technologies to consider including new Precision Dairy Farming technologies. Galligan and Groenendaal (2001) suggested that "the modern dairy producer can be viewed as a manager of an investment portfolio, where various investment opportunities (products, management interventions) must be selected and combined in a manner to provide a profit at a competitive risk to alternative opportunities." Further, dairy managers must consider both biological and economic considerations simultaneously in their decisions. Traditionally, investment decisions have been made using standard recommendations, rules of thumb, consultant advice, or intuition. Thus, more objective methods of investment analysis are needed (Verstegen et al., 1995).

Adoption of sophisticated on-farm decision-making tools has been scant in the dairy industry to this point. Yet, the dairy industry remains a perfect application of decision science because: (1) it is characterized by considerable price, weather, and biological variation and uncertainty, (2) technologies, such as those characteristic of Precision Dairy Farming, designed to collect data for decision making abound, and (3) the primary output, fluid milk, is difficult to differentiate, increasing the need for alternative means of business differentiation. In "Competing on Analytics: The New Science of Winning, "Davenport and Harris (2007) pose that in industries with similar technologies and products, "high performance business processes" are one of the only ways that businesses can differentiate themselves.

Investment analyses of information systems and technologies are common within the general business literature (Bannister and Remenyi, 2000, Lee and Bose, 2002, Ryan and Harrison, 2000, Streeter and Hornbaker, 1993). However, dairy-specific tools examining investment of Precision Dairy Farming technologies are limited (Carmi, 1992, Gelb, 1996, van Asseldonk, 1999), though investment analyses of other dairy technologies abound (Hyde and Engel, 2002). Empirical comparisons of technology before or after adoption or between herds that have adopted a technology and control herds that have not adopted are expensive and biased by other, possibly herd-related differences. As a result, the normative approach, using simulation modeling, predominates in decision support models in animal agriculture (Dijkhuizen et al., 1991). Investing in new agricultural technologies is all too often a daunting and complex task. First, the standard approach using the Net Present Value is often misleading because it does not adequately account for the underlying uncertainties. Second, the incremental costs and benefits of new technologies require complex interactions of multiple variables that are often non-linear and not intuitive. The complexities surrounding investment in Precision Dairy Farming technologies is one example of this type of complex decision.

Ward (1990) listed three benefits to investment in technology: 1) substitutive, replacing human power with machine power, 2) complementary, improving productivity and employee effectiveness through new ways of accomplishing tasks, and 3) innovative, obtaining a competitive edge. In addition to impacts on production, many technologies may also change milk composition, reproductive efficiency, and disease incidences (Galligan and Groenendaal, 2001). In an analysis of an investment opportunity at the dairy level, cash flows are generally uncertain because of biological variability or incomplete knowledge of the system (Galligan and Groenendaal, 2001). The impact that a Precision Dairy Farming technology has on productive and economic performance is difficult to examine because of the changing nature of the decision environment where investments are often one-time investments but returns accrue over a longer period of time (van Asseldonk, 1999, van Asseldonk et al., 1999a, van Asseldonk et al., 1999b, Verstegen et al., 1995, Ward, 1990). Further, benefit streams resulting from investment in a Precision Dairy Farming technology are highly dependent upon the user's ability to understand and utilize the information provided by the new technology (Bannister and Remenyi, 2000). An economic analysis of the value of Precision Dairy Farming technologies requires consideration of the effect of adoption on both quality and timeliness of decisions (Verstegen et al., 1995). Improvements associated with adoption of new Precision Dairy Farming technologies may increase profits directly through improved utilization of data provided by the technology or indirectly through recommendations of consultants utilizing the new information (Tomaszewski et al., 1997). It is difficult, if not impossible to quantify the economic value of personal welfare associated with a proposed change (e.g. free time or prestige) (Otte and Chilonda, 2000). For example, it is nearly impossible to quantify the satisfaction of having a healthy herd, reduction of animal suffering, reduced human health risks, and environmental improvements (Huirne et al., 2003). Despite efforts to formalize the rational decision making analysis of investment in information technologies, many business executives ultimately make their investment decision based on "gut feel" or "acts of faith" (Bannister and Remenyi, 2000, Passam et al., 2003, Silk, 1990). Ultimately, decision making is and should be dependent upon both rational analysis and instinct (Bannister and Remenyi, 2000).

Simulation of Dairy Farms

Mayer et al. (1998) proposed that with the variety of management issues a dairy manager faces in an ever-changing environment (e.g. environmental, financial, and biological), best management strategies cannot be verified and validated with field experiments. As a result, simulation is the only method of "integrating and estimating" these effects (Mayer et al., 1998). Simulations are mathematical models designed to represent a system, such as a dairy farm, for use in decision-making. Simulation models are useful and cost-effective in research that requires complex scenarios involving a large number of variables with large groups of animals over a long period of time under a large range of conditions (Bethard, 1997, Shalloo et al., 2004). The primary advantages of using mathematical computer simulation models in evaluating dairy production issues are the ability to control more variables within the model than with a field trial and the reduced costs associated with this kind of effort (Shalloo et al., 2004, Skidmore, 1990). These economic models can also be useful in evaluating alternatives where very little real data is available yet (Dijkhuizen et al., 1995). Simulating a system is particularly useful when uncertain, complex feedback loops exist (e.g. disease affects production which then impacts other variables further back in the system) (Dijkhuizen et al., 1995). Models that represent system uncertainty, while effectively using available information, provide more realistic insight than models that do not consider a range of responses (Bennett, 1992, Passam et al., 2003).

Simulation or other systemic methods are preferred to capture the complexity of a dairy system as they can evaluate multiple biological and economic factors affecting performance, including management, feeding, breeding, culling, and disease (Skidmore, 1990, Sorensen et al., 1992). Because the dairy system includes environmental, economic, and physical components, accounting for interactions among components and tracing the effects of an intervention through the entire system are essential (Cabrera et al., 2005). Simulation models are ideal for analyzing investment strategies because they can effectively examine improvement in biological parameters based on farm-specific data rather than simple industry averages (Delorenzo and Thomas, 1996, Dijkhuizen et al., 1995, Gabler et al., 2000, Jalvingh, 1992, van Asseldonk et al., 1999b). Simulation of a farm can be accomplished by conducting two simulations, one with and one without a proposed change or intervention and then comparing these simulations to examine the impact on biological or economic parameters of interest (van Asseldonk, 1999). The output of a series of simulations provides a range of results, more realistically depicting biological variability than simple models (Marsh et al., 1987).

Risk and uncertainty are major considerations within a dairy production system because of the random nature of milk production, biology, disease, weather, input costs, and milk prices (Delorenzo and Thomas, 1996). This risk and uncertainty represents a major portion of the difficulty and complexity of managing a dairy operation (Huirne, 1990). Uncertainty must be considered in decision-making to avoid biased estimates and erroneous decisions (Kristensen and Jorgensen, 1998). Future costs and returns are always uncertain (Lien, 2003). Within precision agriculture, accurate representation of risk associated with technology adoption is critical in the decision making process (Marra et al., 2003).

When managers do not have sufficient information to assess the risk outcomes of decisions, they use subjective probabilities based on past experiences and their own judgment (Huirne, 1990). In most situations, decision makers are primarily concerned with the chances of the realized returns from an investment being less than predicted (Galligan et al., 1987). The ability of a model to reflect real world conditions increases with consideration of more variables (Jalvingh, 1992). Nevertheless, to ensure that the model remains practical and reasonable, only variables with the most influence on the final desired outcome should be entered into the model as random (Jalvingh, 1992, Lien, 2003).

Purdue/Kentucky Research Model

Bewley et al. (2010b) developed a simulation model of a dairy farm to evaluate investments in precision dairy farming technologies by examining a series of random processes over a ten-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 1. 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.

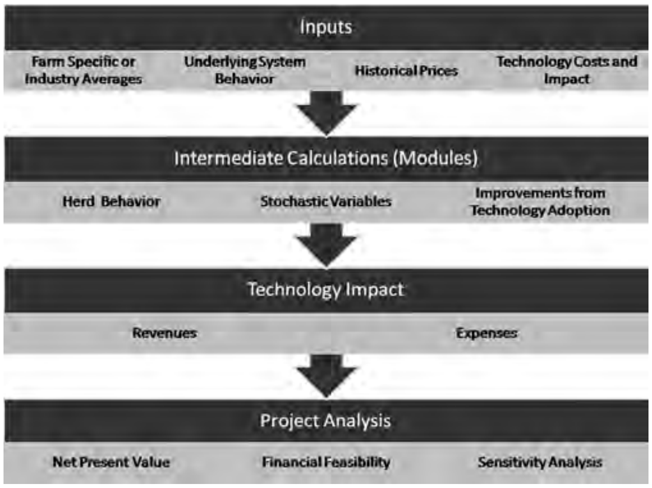

Figure 1. Diagram depicting general flow of information within the model

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 2), 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 1 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.

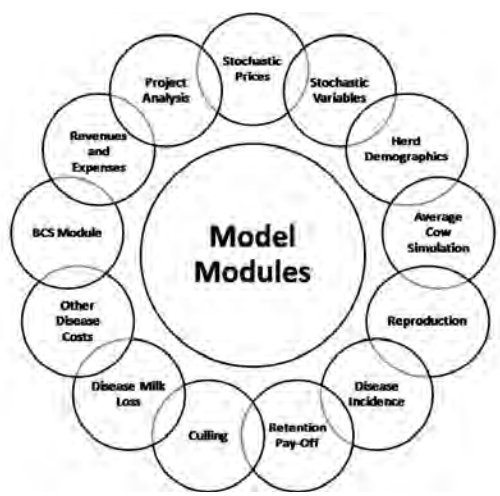

Figure 2. Diagram of model modules

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

To show how it can be used practically, this model was used for an investment analysis of automatic body condition scores on dairy farms (Bewley et al., 2010a). Automated body condition scoring (**BCS**) through extraction of information from digital images has been demonstrated to be feasible; and commercial technologies are being developed (Bewley et al., 2008). The primary objective of this research 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, and 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. Further details of model inputs and assumptions may be obtained from the author.

Net present value (**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.

Profitability Analysis

For the small likelihood of improvement simulation, 13.1% of simulation iterations resulted in a positive NPV whereas this same number was 87.8% for the scenario with a definite improvement. 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 13.1% or 87.8% 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 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., 1999b). 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 ≤ 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 3). 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.

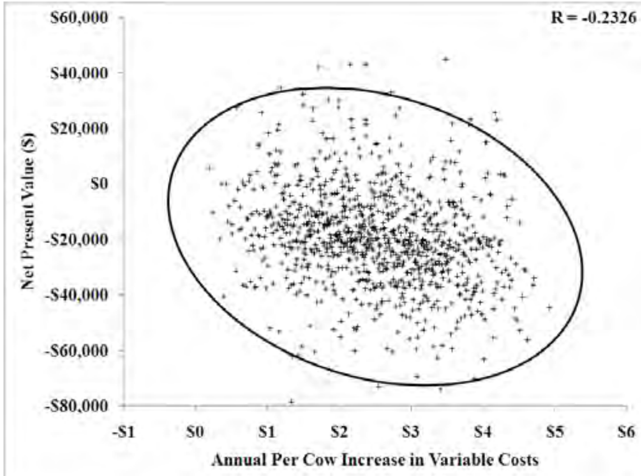

Figure 3. Scatter plot of Net Present Value versus annual percentage increase in variable costs (for simulation using all expert opinions provided)

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 4. 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.

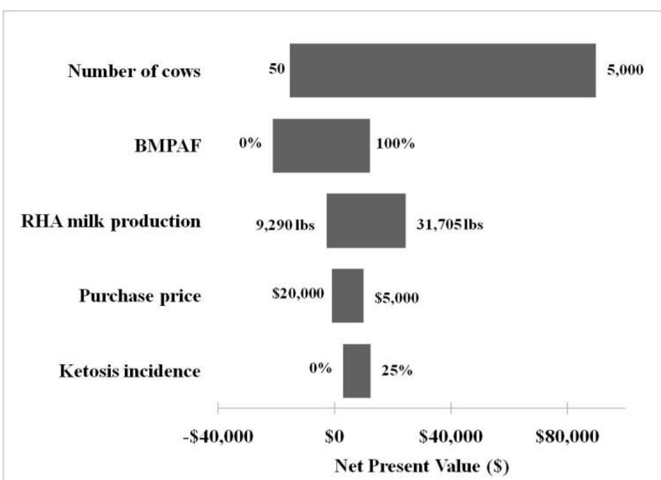

Figure 4. Tornado diagrams for inputs affecting 95th percentile of Net Present Value for simulations using the estimates of all survey respondents[1]

[1] BMPAF is the Best Management Practice Adherence Factor, RHA milk production is rolling herd average milk production in lbs.

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.

Adoption Considerations

The list of Precision Dairy Farming technologies used for animal status monitoring and management continues to grow. Despite widespread availability, adoption of these technologies in the dairy industry has been relatively sparse thus far (Gelb et al., 2001, Huirne et al., 1997). Perceived economic returns from investing in a new technology are always a factor influencing technology adoption. Additional factors impacting technology adoption include degree of impact on resources used in the production process, level of management needed to implement the technology, risk associated with the technology, institutional constraints, producer goals and motivations, and having an interest in a specific technology (Dijkhuizen et al., 1997, van Asseldonk, 1999). Characteristics of the primary decision maker that influence technology adoption include age, level of formal education, learning style, goals, farm size, business complexity, increased tenancy, perceptions of risk, type of production, ownership of a non-farm business, innovativeness in production, average expenditure on information, and use of the technology by peers and other family members. Research regarding adoption of Precision Dairy Farming technologies is limited, particularly within North America.

To remedy this, a five-page survey was distributed to all licensed milk producers in Kentucky (N=1074) on July 1, 2008. Two weeks after the first mailing, a follow-up postcard was mailed to remind producers to return the survey. On August 1, 2008, the survey was resent to producers who had not returned the survey. A total of 236 surveys were returned; 7 were omitted due to incompletion leaving 229 for subsequent analyses (21%). The survey consisted of questions covering general farm descriptive demographics, extension programming, and decision making behavior. With regard to Precision Dairy Farming the following question was presented to survey participants: *“Adoption of automated monitoring technologies (examples: pedometers, electrical conductivity for mastitis detection) in the dairy industry has been slow thus far. Which of the following factors do you feel have impacted these modest adoption rates? (check ALL that apply).”* Data were entered into an online survey tool (KeySurvey, Braintree, MA). Statistical analyses were conducted using SAS® (Cary, NC). Surveys were categorized by herd size, production system, operator age, and production level. Least squares means among categories were calculated for quantitative variables using the GLM procedure of SAS®. Statistical differences were considered significant using a 0.05 significance level using Tukey’s test for multiple comparisons. For qualitative variables, χ^2 analyses were conducted using the FREQ procedure of SAS®. Statistical differences were considered significant at a 0.05 significance level.

Among the 229 respondents, mean herd size was 83.0 ± 101.8 cows and mean producer age was 50.9 ± 12.9. Reasons for modest adoption rates of Precision Dairy Farming technologies and dairy systems software are presented in Table 1. The reasons selected by the highest percentage respondents were (1) not being familiar with technologies that are available (55%), (2) undesirable cost to benefit ratios (42%) and (3) too much information provided without knowing what to do with it (36%%). The high percentage of producers who indicated they were unfamiliar with available technologies indicates that marketing efforts may improve technology adoption. Actual or perceived economic benefits appear to influence adoption rates demonstrating the need for economic models to assess technology benefits and re-examination of retail product prices. As herd size increased, the percentage of producers selecting "poor technical support/training" and "compatibility issues" increased ($P < 0.05$), which may be reflective of past negative experiences. In developing technologies, manufacturers should work with end-users during development and after product adoption to alleviate these customer frustrations. Few significant differences were observed among age groups, though the youngest producers were more likely to select "better alternatives/easier to accomplish manually." Prior to technology development, market research should be conducted to ensure that new technologies address a real need. Utilizing this insight should help industry Precision Dairy Farming technology manufacturers and industry advisors develop strategies for improving technology adoption. Moreover, this information may help focus product development strategies for both existing and future technologies.

Table 1. Factors influencing slow adoption rates of Precision Dairy Farming technologies

Factor	N	Percent
Not familiar with technologies that are available	101	55%
Undesirable cost to benefit ratio	77	42%
Too much information provided without knowing what to do with it	66	36%
Not enough time to spend on technology	56	31%
Lack of perceived economic value	55	30%
Too difficult or complex to use	53	29%
Poor technical support/training	52	28%
Better alternatives/easier to accomplish manually	43	23%
Failure in fitting with farmer patterns of work	40	22%
Fear of technology/computer illiteracy	39	21%
Not reliable or flexible enough	33	18%
Not useful/does not address a real need	27	15%
Immature technology/waiting for improvements	18	10%
Lack of standardization	17	9%
Poor integration with other farm systems/software	12	7%
Compatibility issues	12	7%

CONCLUSIONS AND OUTLOOK

Though Precision Dairy Farming is in its infancy, new Precision Dairy Farming technologies are introduced to the market each year. As new technologies are developed in other industries, engineers and animal scientists find applications within the dairy industry. More importantly, as these technologies are widely adopted in larger industries, such as the automobile or personal computing industries, the costs of the base technologies decrease making them more economically feasible for dairy farms. Because the bulk of research focused on Precision Dairy Farming technologies is conducted in research environments, care must be taken in trying to transfer these results directly to commercial settings. Field experiments or simulations may need to be conducted to alleviate this issue. Because of the gap between the impact of Precision Dairy Farming technologies in research versus commercial settings, additional effort needs to be directed toward implementation of management practices needed to fully utilize information provided by these technologies. To gain a better understanding of technology adoption shortcomings, additional research needs to be undertaken to examine the adoption process for not only successful adoption of technology but also technology adoption failures.

Before investing in a new technology, a formal investment analysis should be conducted to make sure that the technology is right for your farm's needs. 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 stochastic simulation 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 our model case study 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. Precision dairy farming technologies provide tremendous opportunities for improvements in individual animal management on dairy farms. In the future, Precision Dairy Farming technologies may change the way dairy herds are managed.

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Precision dairy monitoring opportunities and challenges

Dairy

Precision Dairy

JEFFREY BEWLEY

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Precision Dairy Monitoring

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Precision Dairy Monitoring Applications

- Estrus Detection
- Mastitis Detection
- Fresh Cow Disease Detection
- Lameness Detection
- Calving Detection
- Genetic Traits
- Management Monitoring


BIG DATA
VOLUME
DATA SIZE
VELOCITY
SPEED OF CHANGE
VARIETY
DIFFERENT FORMS OF DATA SOURCES
VERACITY
UNCERTAINTY OF DATA


Second Green Revolution?
Deloitte University Press
Deloitte Review
FROM DIRT TO DATA
The second green revolution and the Internet of Things
#DeloitteReview
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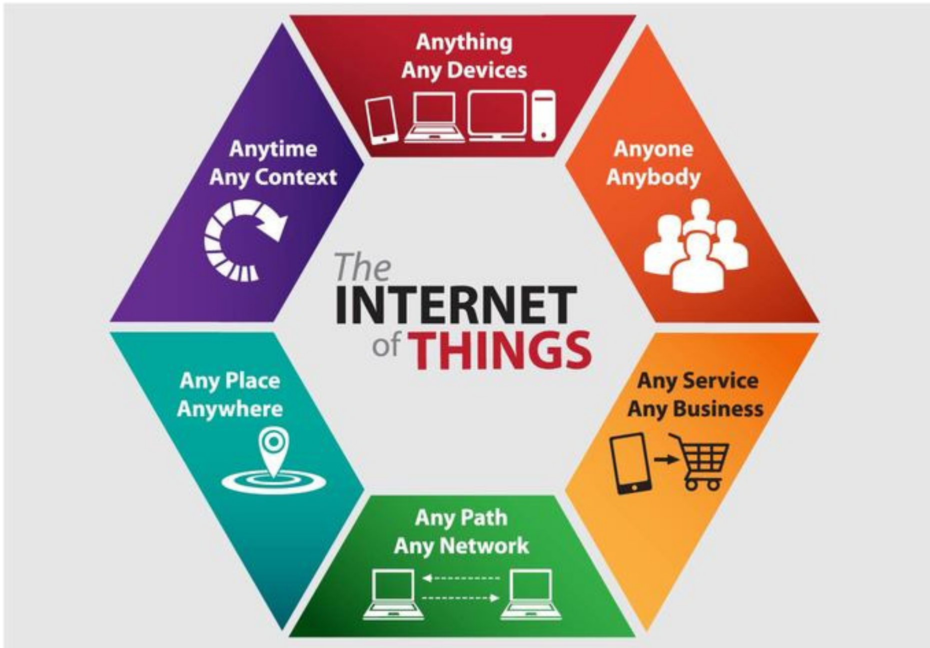
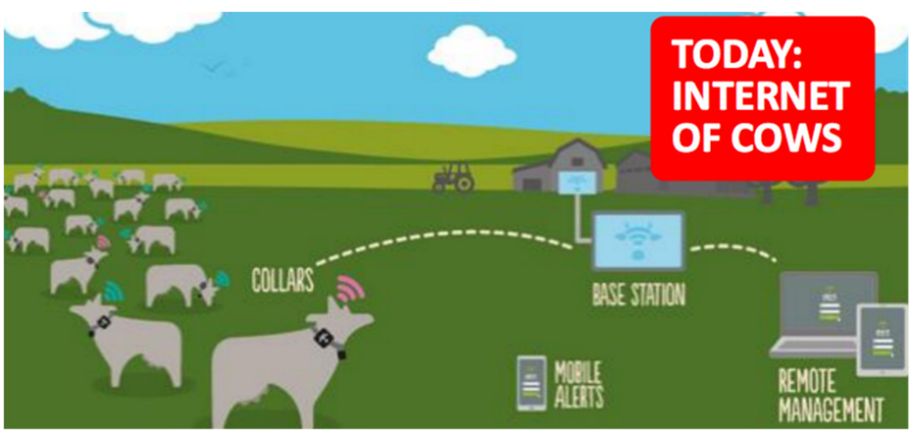
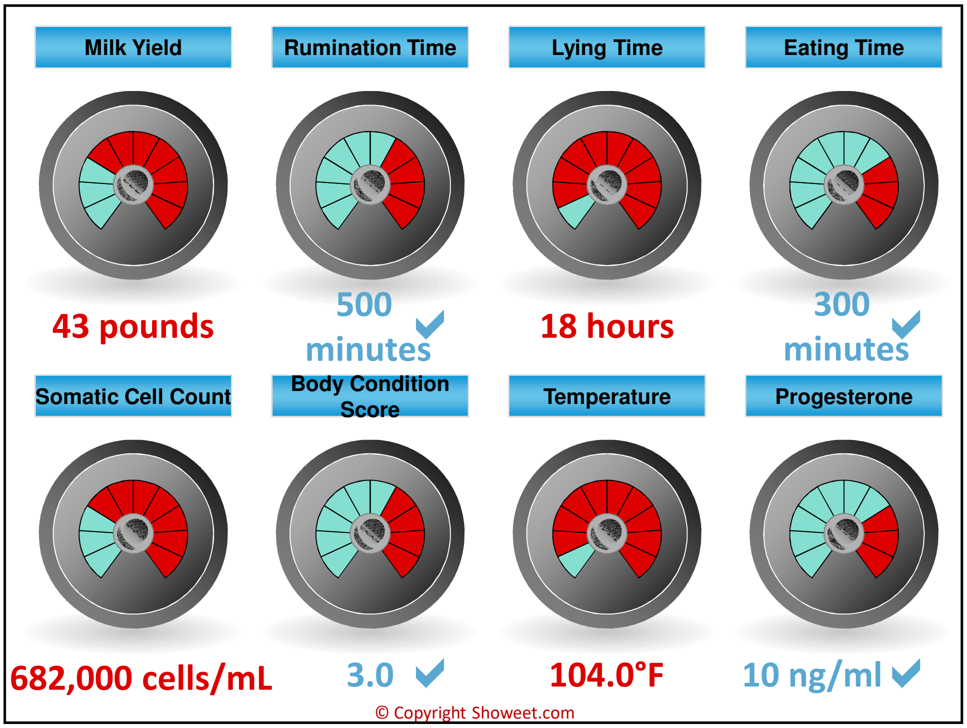

Anything
Any Devices
Anyone
Anybody
Any Service
Any Business
Any Path
Any Network
Any Place
Anywhere
Anytime
Any Context
The
INTERNET
of THINGS


TODAY:
INTERNET
OF COWS
COLLARS
BASE STATION
MOBILE
ALERTS
REMOTE
MANAGEMENT


Milk Yield
Rumination Time
Lying Time
Eating Time
43 pounds
500 minutes
18 hours
300 minutes
Somatic Cell Count
Body Condition Score
Temperature
Progesterone
682,000 cells/mL
3.0
104.0°F
10 ng/ml
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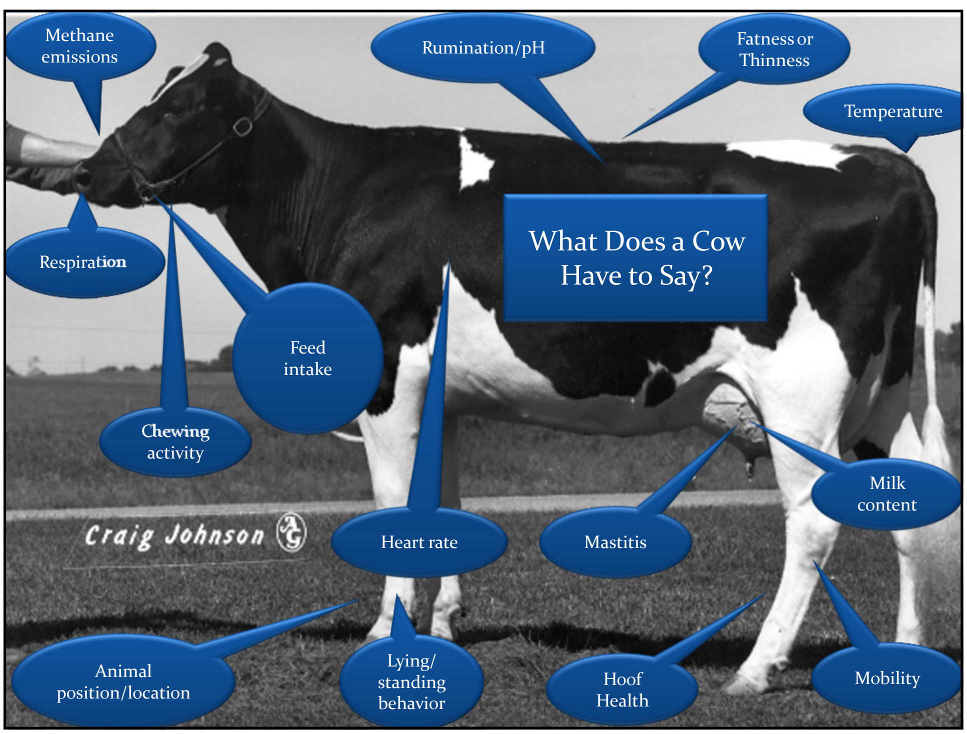
Methane emissions
Rumination/pH
Fatness or Thinness
Temperature
Respiration
What Does a Cow Have to Say?
Feed intake
Chewing activity
Milk content
Craig Johnson
Heart rate
Mastitis
Animal position/location
Lying/ standing behavior
Hoof Health
Mobility

Ideal Technology

- Explains an underlying biological process
- Can be translated to a meaningful action
- Cost-effective
- Flexible, robust, reliable
- Simple and solution focused
- Readily available information

The Options Are Endless


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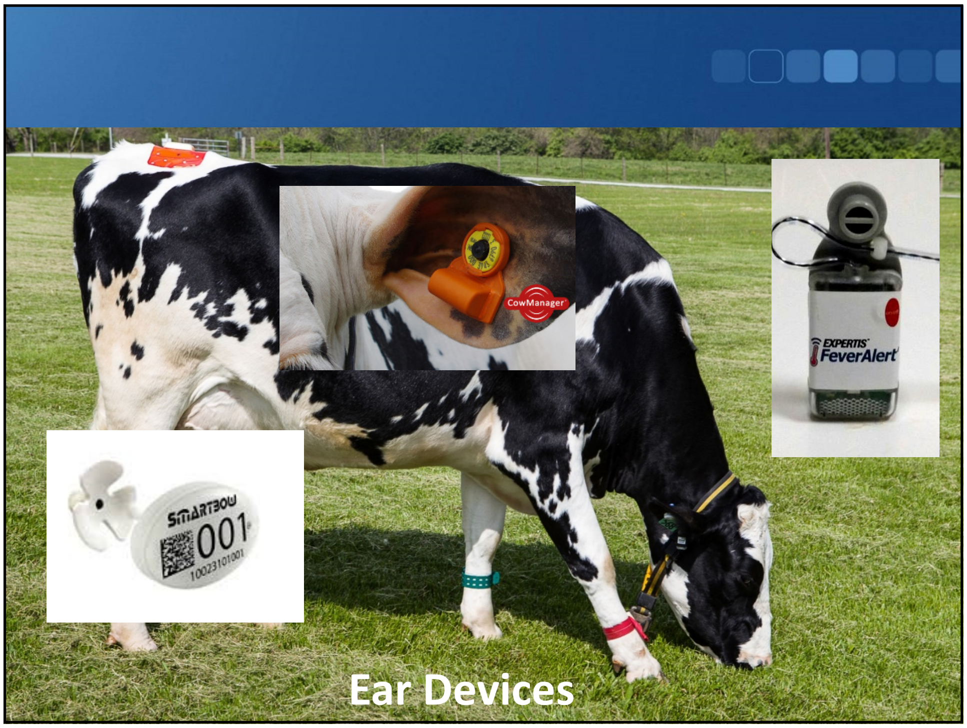
Dairy
Precision Dairy
INNOVATIVE TECHNOLOGY
IT STARTS WITH US!


ICEQUBE
Leg Devices

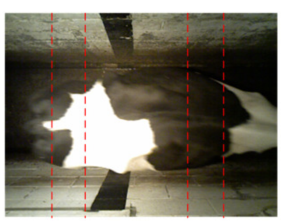

CowManager
EXPERTIS
FeverAlert
SMARTBOW
001
10023101001
Ear Devices

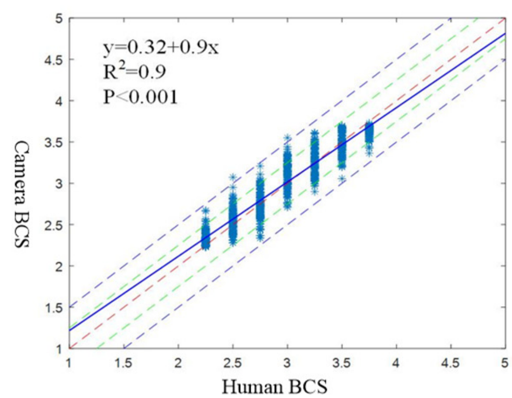

MooMonitor+
Silent
Herdsman
SCR by Allflex
Make every cow count
Neck Devices


BellaAg
smaXtec
Rumen Devices


Moocall
Medria
Calving Devices

Kentucky BCS Work





Over 99% cows had mean absolute error lower than 0.25

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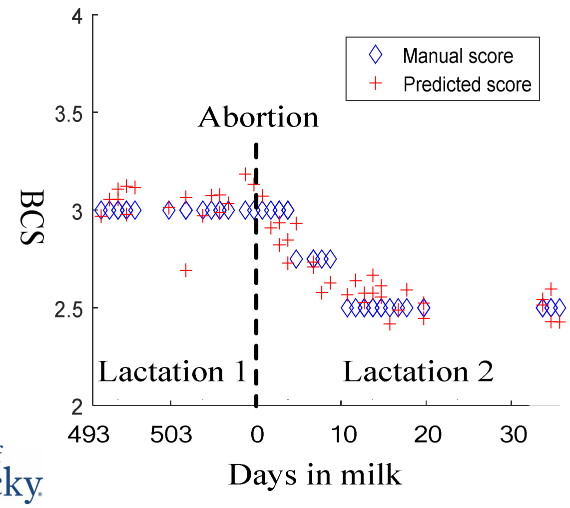
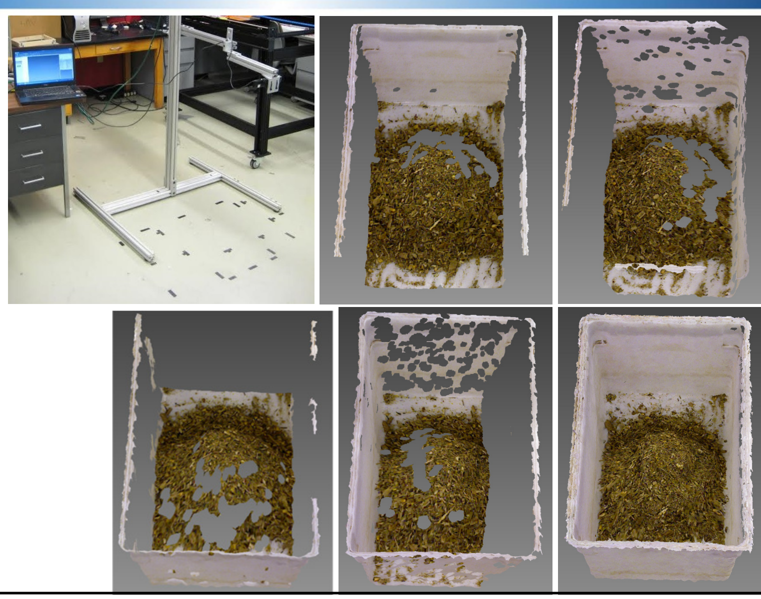
Zhao et al., 2017

Tracking BCS Changes

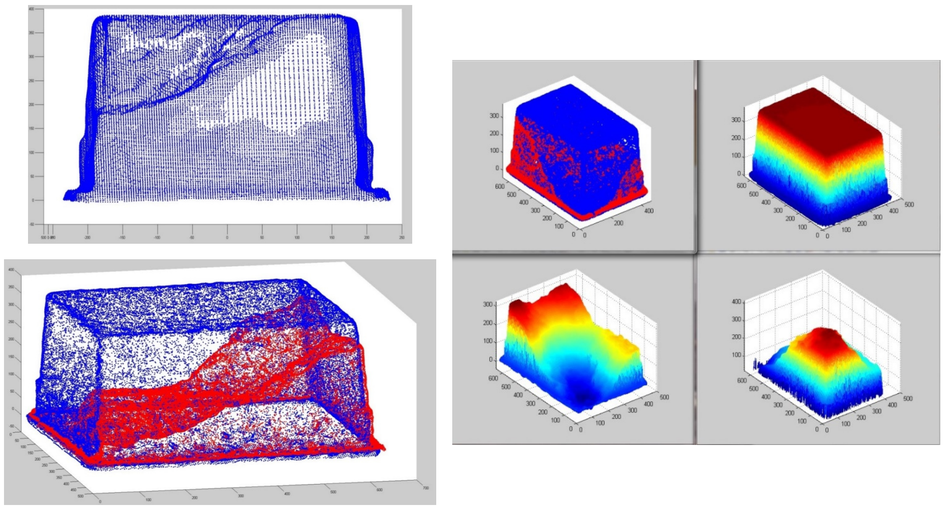


Zhao et al., 2017

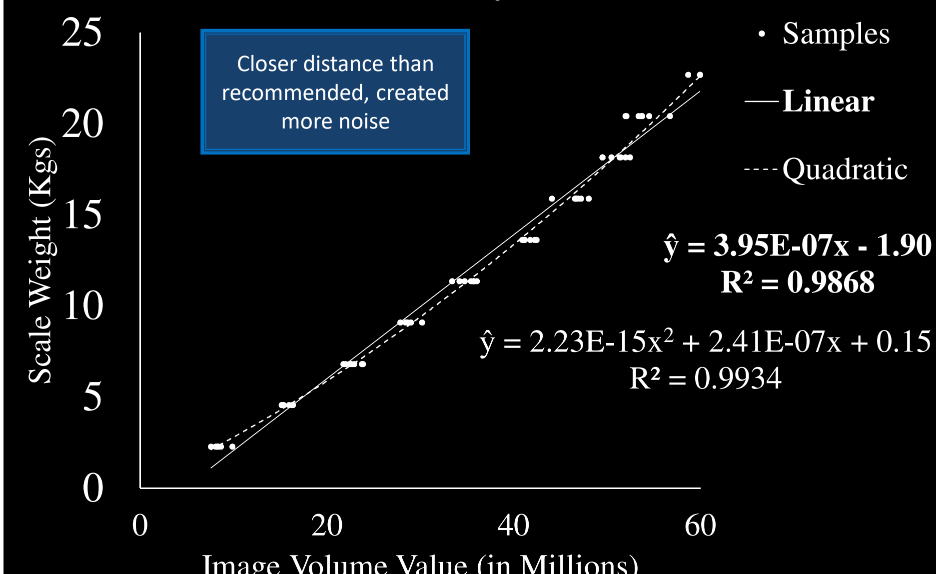
Imaging System

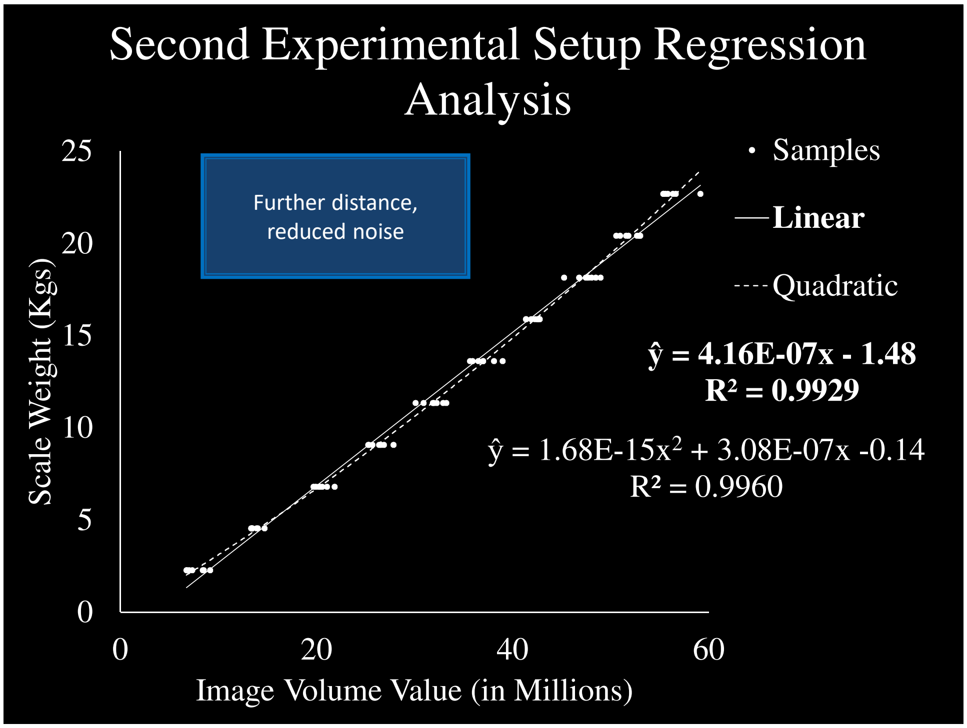


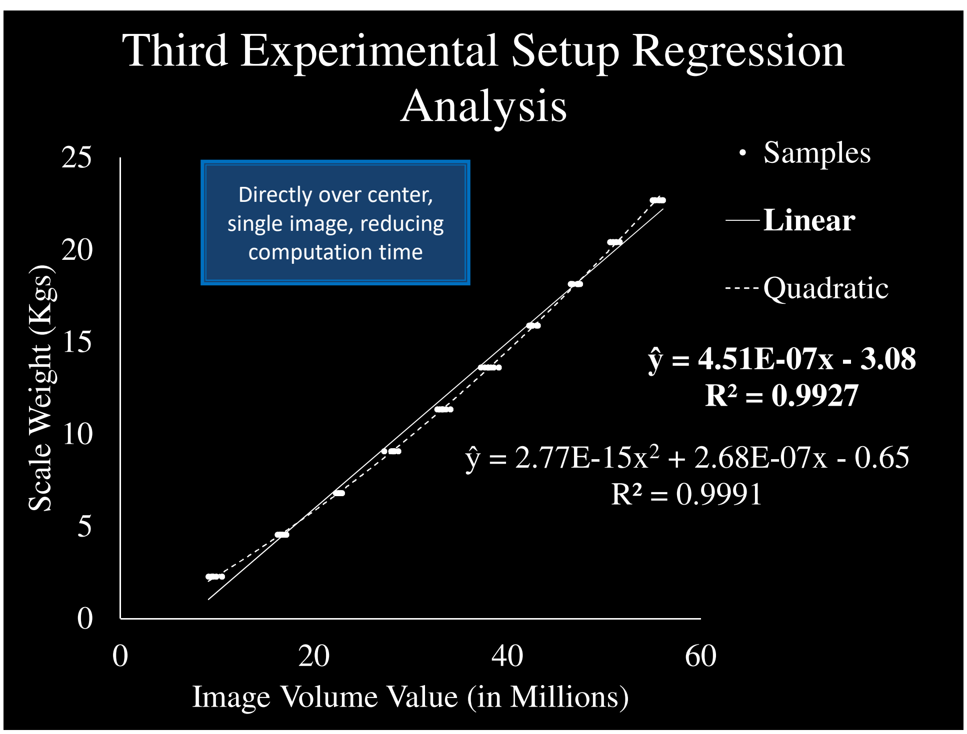
Processing



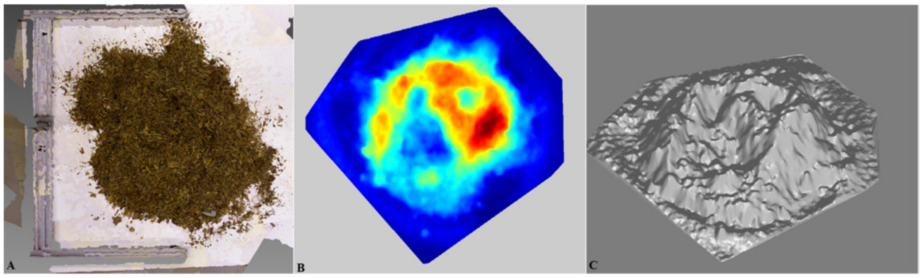
First Experimental Setup Regression Analysis




Second Experimental Setup Regression Analysis
Further distance, reduced noise
Samples
Linear
Quadratic
ŷ = 4.16E-07x - 1.48
R² = 0.9929
ŷ = 1.68E-15x² + 3.08E-07x -0.14
R² = 0.9960
Scale Weight (Kgs)
0
5
10
15
20
25
0
20
40
60
Image Volume Value (in Millions)


Third Experimental Setup Regression Analysis
Directly over center, single image, reducing computation time
Samples
Linear
Quadratic
ŷ = 4.51E-07x - 3.08
R² = 0.9927
ŷ = 2.77E-15x² + 2.68E-07x - 0.65
R² = 0.9991
Scale Weight (Kgs)
0
5
10
15
20
25
0
20
40
60
Image Volume Value (in Millions)

Future Goals



- Feed on the ground beneath the camera
- Depth data of the feed surface differenced from the floor depth data
- Side view of the feed depth data shown as a surface texture
- Multi-camera real feed bunk

Video Behavior

University of Kentucky Research

Lying, Rumination, and Feeding Validation

- Technologies :
  - AfiAct Pedometer Plus
  - Cowalert IceQube
  - CowManager Sensoor
  - Smartbow
  - Track a))) Cow

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Borchers et al., 2016

Lying Behavior

Technology	Number of cows	Correlation to visual observations (r)[1]
CowAlert IceQube	48	1.00**
Track a Cow	44	1.00**
AfiAct Pedometer Plus[2]	48	1.00**

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Feeding Behavior

Technology	Number of cows	Correlation to visual observations (r)[1]
CowManager SensOor	46	0.87**
Track a Cow	41	0.93**

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Rumination Time

Technology	Number of cows	Correlation to visual observations (r)[1]
CowManager SensOor	46	0.69**
Smartbow	46	0.96**

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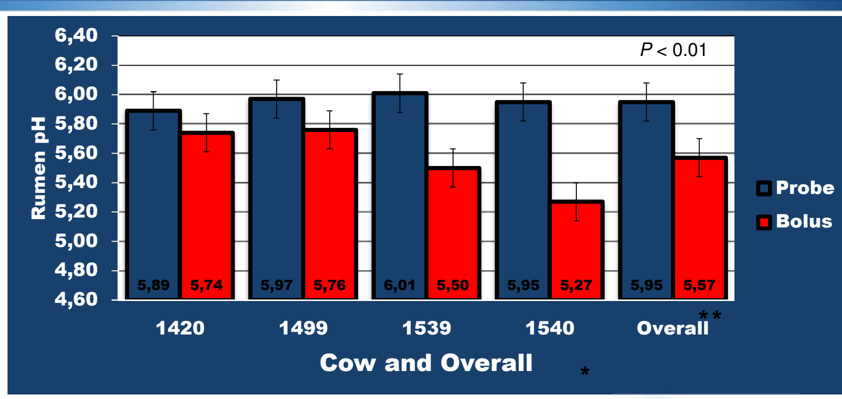
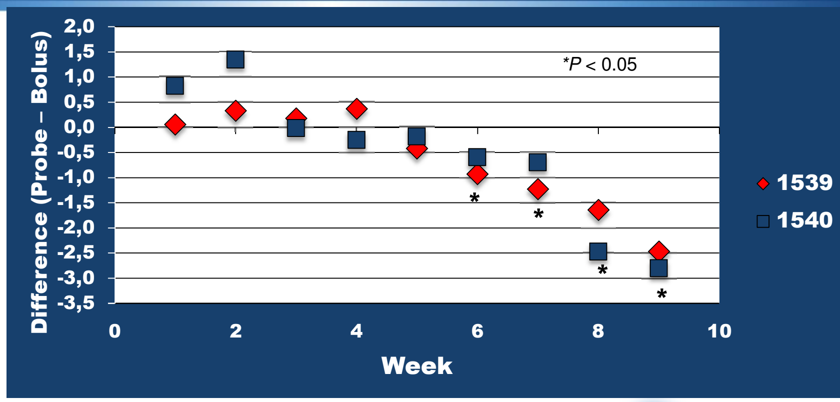
Rumen pH Validation



Rumen pH measured by the bolus was consistently and significantly higher than bench top pH meter

Weatherly et al., 2014

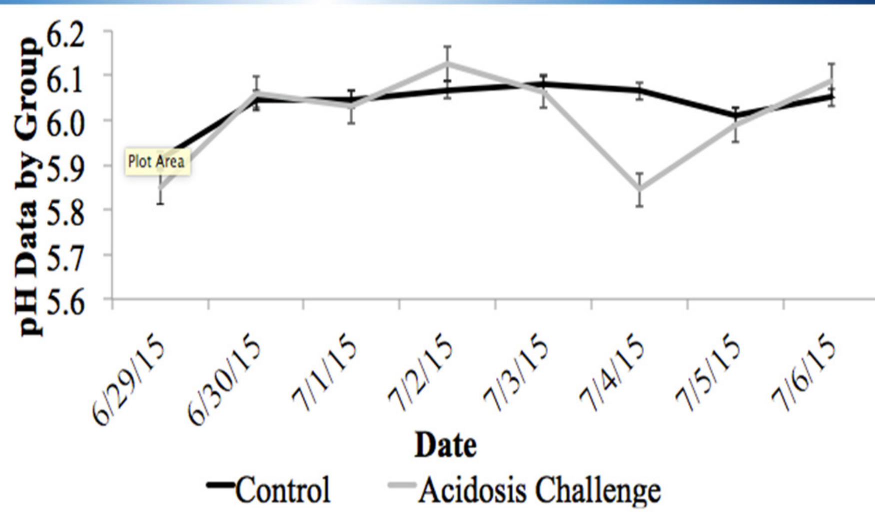
Rumen pH Drift



Rumen pH between two techniques not different until week 6, when bolus drift started

Weatherly et al., 2014

pH Challenge-Smaxtec



Skelton et al., 2016

University of Kentucky Research

Early Disease Detection

- Detect diseases earlier than with visual observation alone
- Improve individual cow treatment results
- Indicate a larger, herd-level, problem leading to improved prevention strategies

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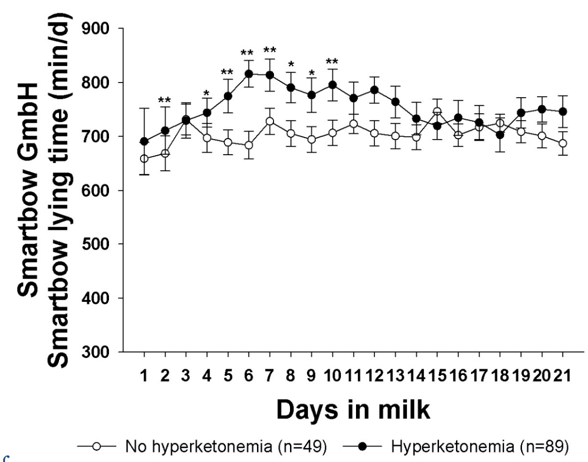
Hyperketonemia: Increased lying



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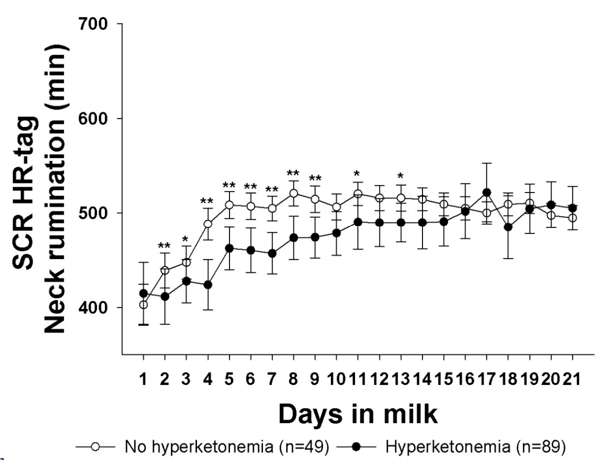
Tsai et al. 2016, unpublished

Hyperketonemia: Increased rumination time



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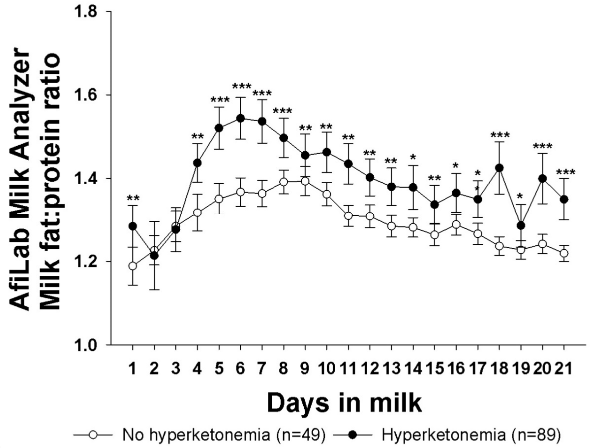
Tsai et al. 2016, unpublished

Hyperketonemia: Higher fat:protein



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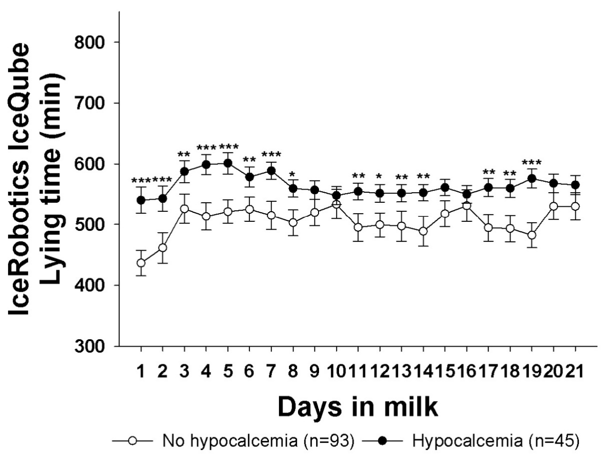
Tsai et al. 2016, unpublished

Hypocalcemia: Increased lying



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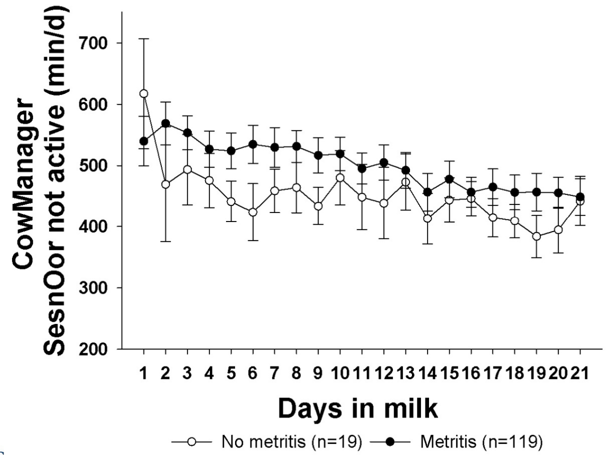
Tsai et al. 2016, unpublished

Metritis: Increased lying



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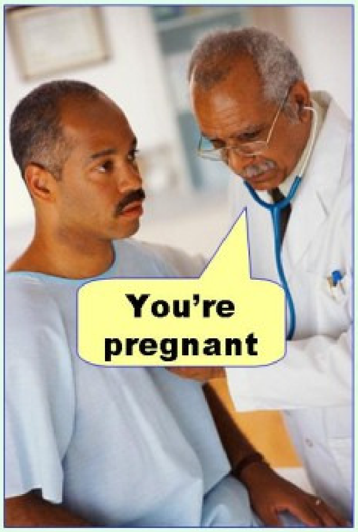
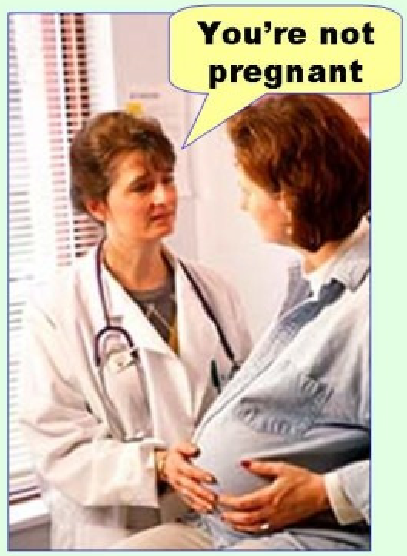
Tsai et al. 2016, unpublished

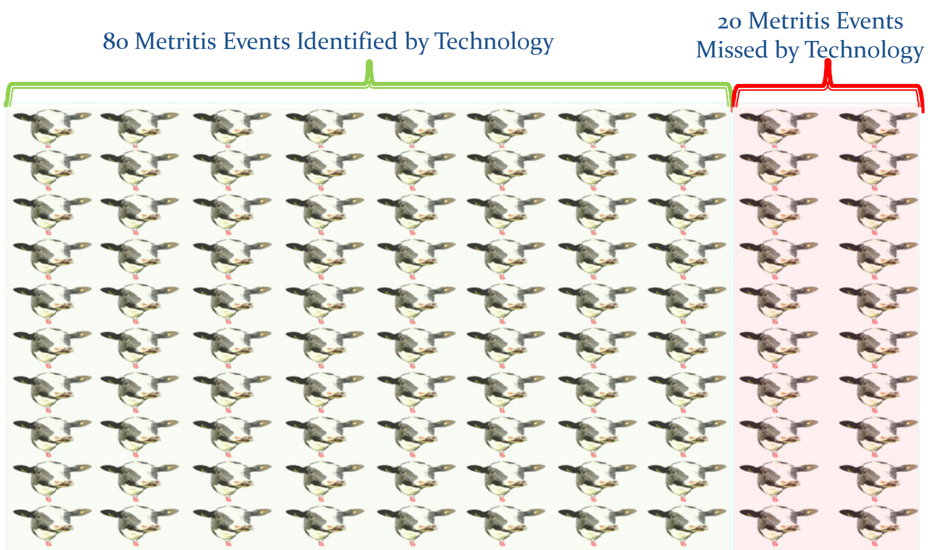
Type I error
(false positive)



Type II error
(false negative)

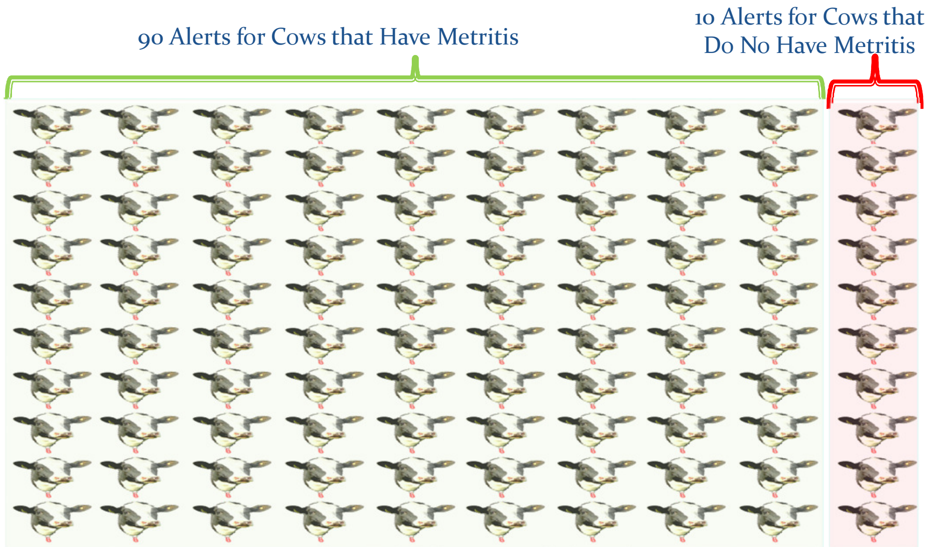


How Many Cows With Condition Do We Find?



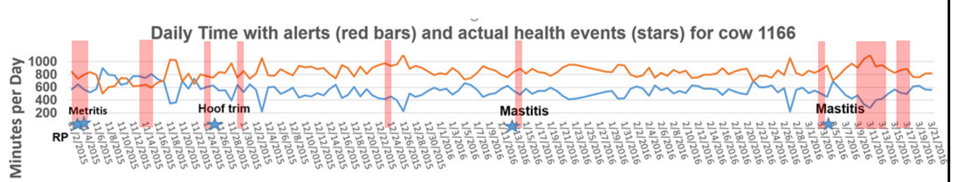
Example: 100 metritis events

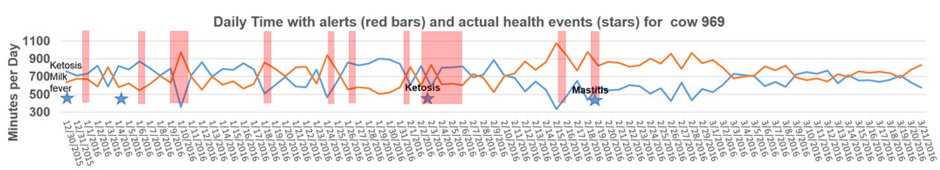
How Many Alerts Coincide with an Actual Event?



Example: 100 metritis alerts

Timeline Alert/Event Comparisons





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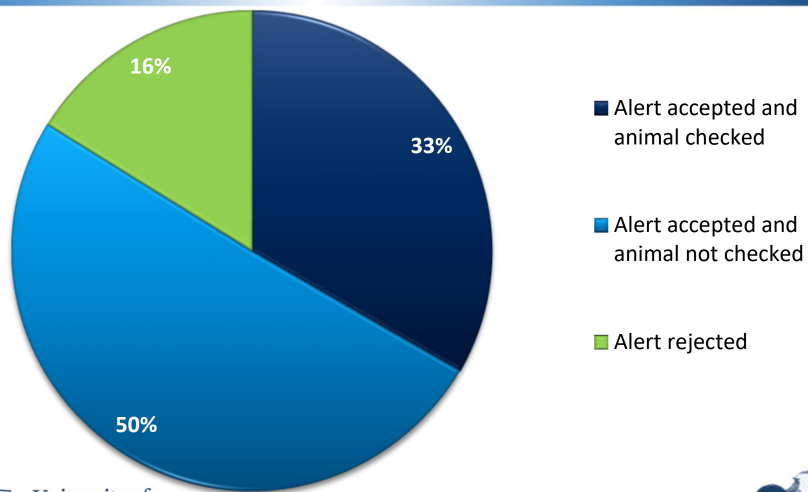
Eckelkamp et al., 2017

Farmer Handling of Sensor Alerts



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Eckelkamp et al., 2017

Health status summary of cows enrolled in the intensive health cow checks from 1 to 14

Variable	Subclinical ketosis	Hypocalcemia	Clinical metritis	No disease
n cows diagnosed, cow days	208	176	30	-
Mean ± SD rumination time, h/d	5.49 ± 1.93	5.20 ± 1.77	5.25 ± 2.21	6.08 ± 1.90
Mean ± SD reticulorumen temperature, °C	39.04 ± 1.16	38.99 ± 0.59	39.36 ± 0.56	39.05 ± 1.26
Mean ± SD lying time, h/d	10.37 ± 3.43	10.33 ± 3.94	11.41 ± 3.11	9.51 ± 3.13
Mean ± SD milk yield, kg/d	27.60 ± 8.20	25.09 ± 8.67	25.45 ± 10.65	28.92 ± 7.39

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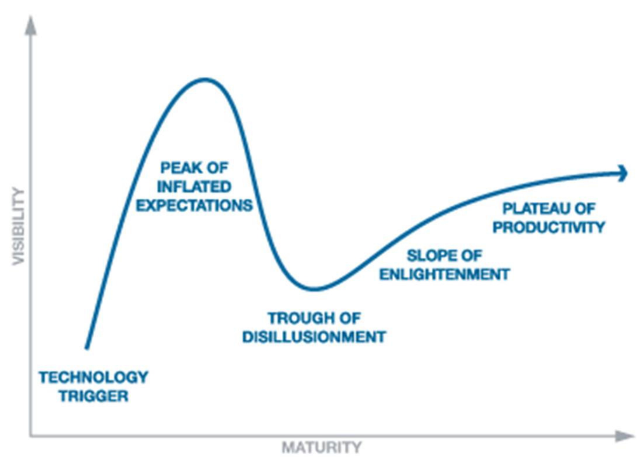
Stone et al. 2016, unpublished

Sensitivity and specificity of rumination time, activity, reticulorumen temperature, lying time, and lying bouts on each disease using different alert thresholds for disease detection

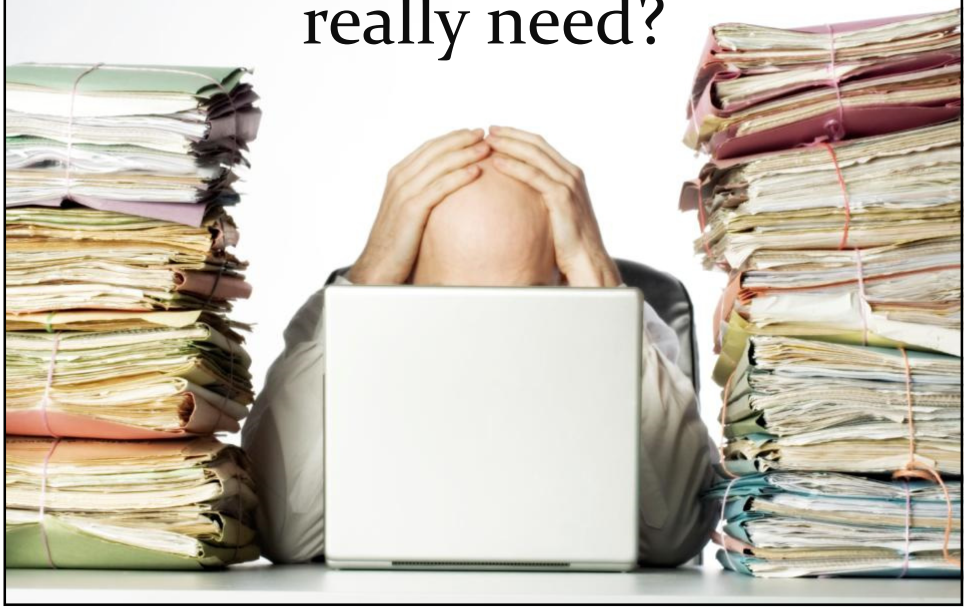
Disease	Sensitivity (%)	Specificity (%)	Accuracy
Subclinical ketosis	98	6	94
	55	91	57
Hypocalcemia	97	8	55
	85	22	55
Clinical metritis	86	52	86
	67	85	67

Stone et al. 2016, unpublished

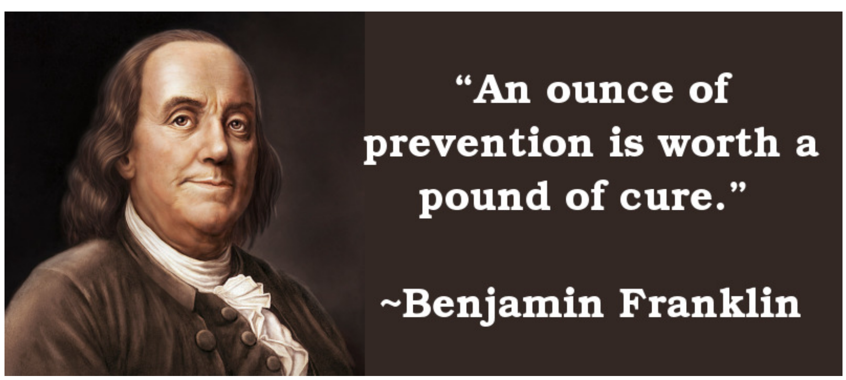
Gartner Product Life Cycle



How much information do we really need?



Are we focused too heavily on disease detection?



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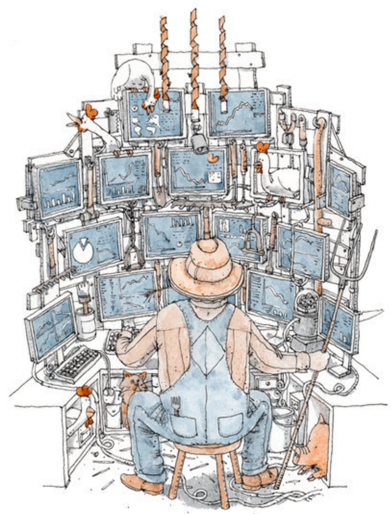
Data Integration



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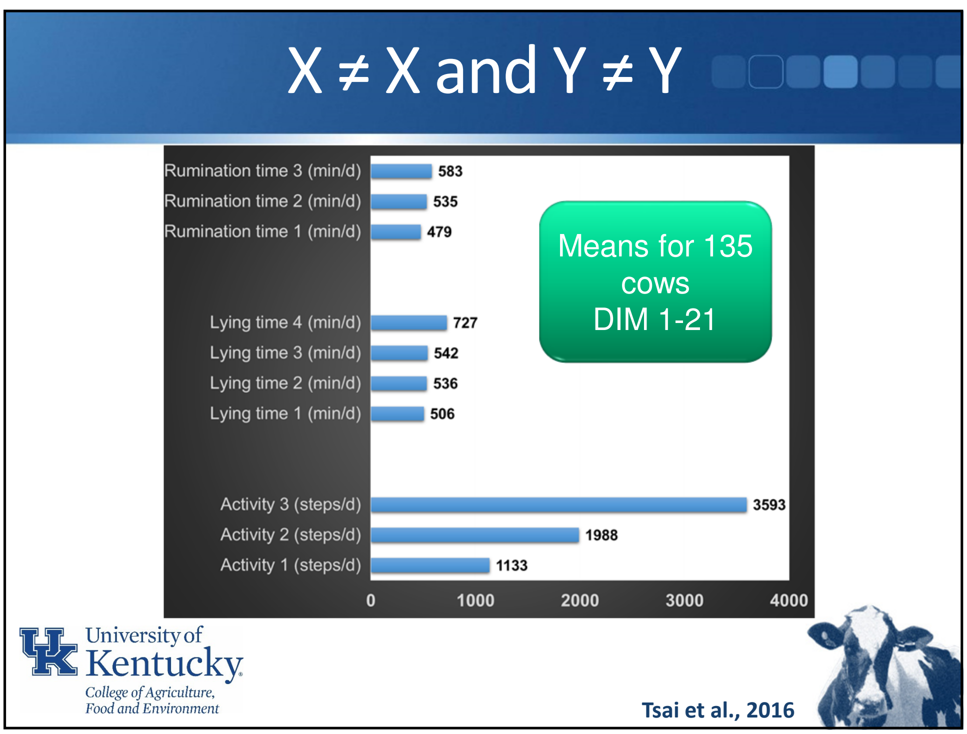
College of Agricu...
Food and Environment

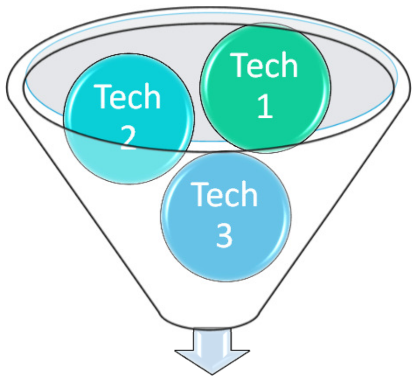
Understanding Technology Economics

CAT5 Cable is a Raccoon Delicacy


WARNING:
Lightning will strike the same technology twice


X ≠ X and Y ≠ Y
Rumination time 3 (min/d)
Rumination time 2 (min/d)
Rumination time 1 (min/d)
Lying time 4 (min/d)
Lying time 3 (min/d)
Lying time 2 (min/d)
Lying time 1 (min/d)
Activity 3 (steps/d)
Activity 2 (steps/d)
Activity 1 (steps/d)
583
535
479
727
542
536
506
3593
1988
1133
0
1000
2000
3000
4000
Means for 135 cows
DIM 1-21
University of Kentucky
College of Agriculture, Food and Environment
Tsai et al., 2016

Disappearing Data



847 cow days (29%) out of possible 2898

- 138 cows
- DIM 1 to 21
- 2898 cow days
- 7 technologies

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Tsai et al., 2016

Other Cautions

- Huge within cow and within herd variation
- Many management factors and environmental conditions affect these variables
- Some times tags randomly stop reading
- Tag placement is important
- Group/pen changes affect behaviors
- Some cows don't read the book
- Not all changes are linear

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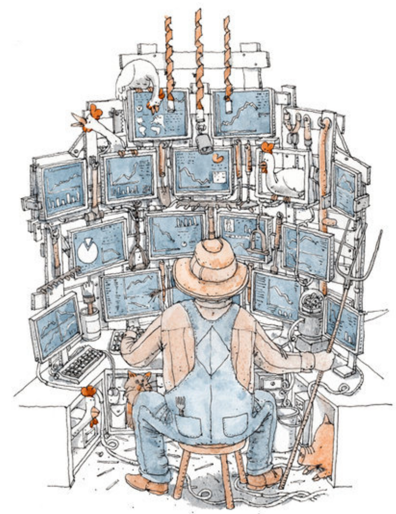
6 Questions Producers Should Ask

1. What are the sensitivity/specificity for condition of interest?
2. What percent of devices fail per year?
3. What is the warranty policy?
4. What is the policy for upgrading to new versions of devices?
5. What are full costs (hardware, devices, maintenance, data storage)?
6. What protocols are available for handling alerts?

1. Data Integration



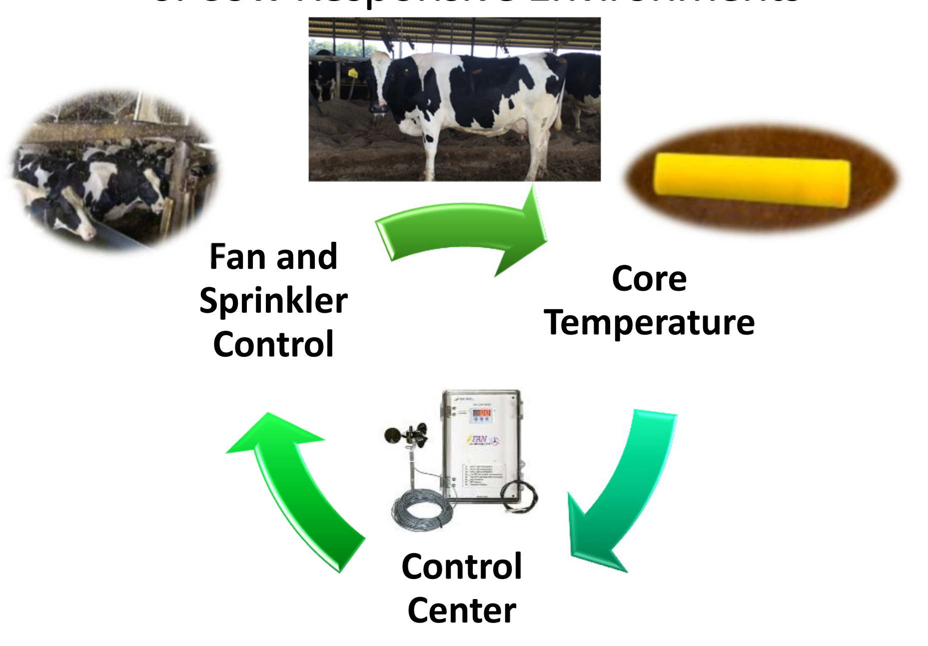
2. Understanding Technology Economics

4. Farmer User Groups

5. Group or Herd Level Data

- Most useful for within group or within herd changes
- May be useful for cohort comparisons
- Keep in mind natural variation and lag
- Be extremely cautious comparing across herds
- Question conventional wisdom

6. Cow Responsive Environments



7. Calf Monitoring

- Calf feeder data
- Wearables
- Physiology?

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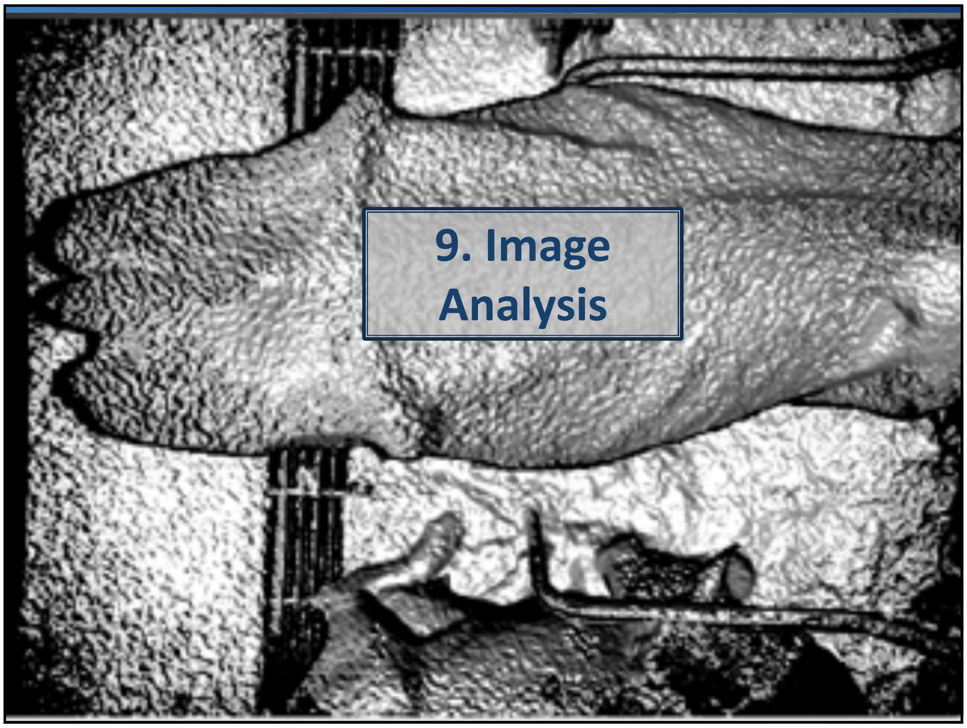
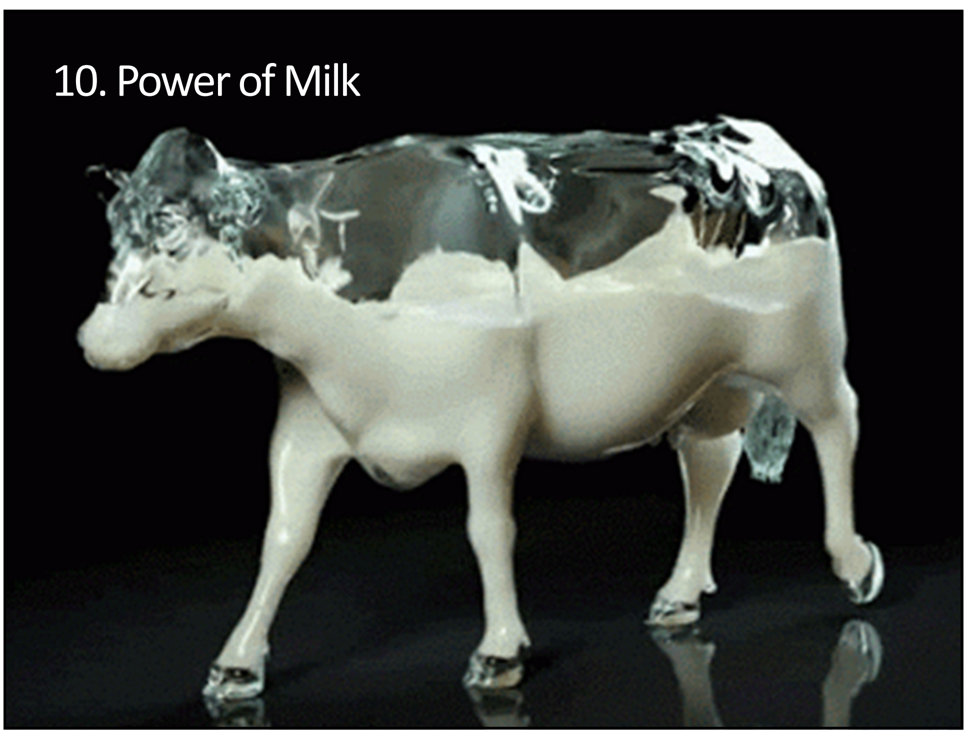
8. Genetic Evaluations

- May provide information previously unavailable for genetic evaluations
- New or improved traits (i.e. feed intake, lameness, BCS, heat tolerance, fertility)
- Improved data accuracy (i.e. yield, fat, protein, SCC, health traits)
- Synergies with genomics


9. Image
Analysis


10. Power of Milk


Questions?
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Lexington, KY 40546-0215
Phone: 859-257-7543
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Élevage laitier de précision : défis et opportunités

Dairy
Precision Dairy

JEFFREY BEWLEY

Amanda Stone, Randi Black, Barbara Wadsworth, Di Liang, Karmella Dolecheck, Matthew Borchers, Lauren Mayo, Nicky Tsai, Maegan Weatherly, Melissa Cornett, Samantha Smith, Megan Hardy, Jenna Klefot, Juha Hietaoja, Barbara Wolfger, Elizabeth Eckelkamp, Savannah Meade, Carissa Truman, Alison DiGennaro, Emory Thomas, Amanda Lee, Michele Jones, Leen Leenaerts, Kevin Zhao, Sarah Mac, Tyler Mark, Brittany Core, Joey Clark, Amelia Fendley

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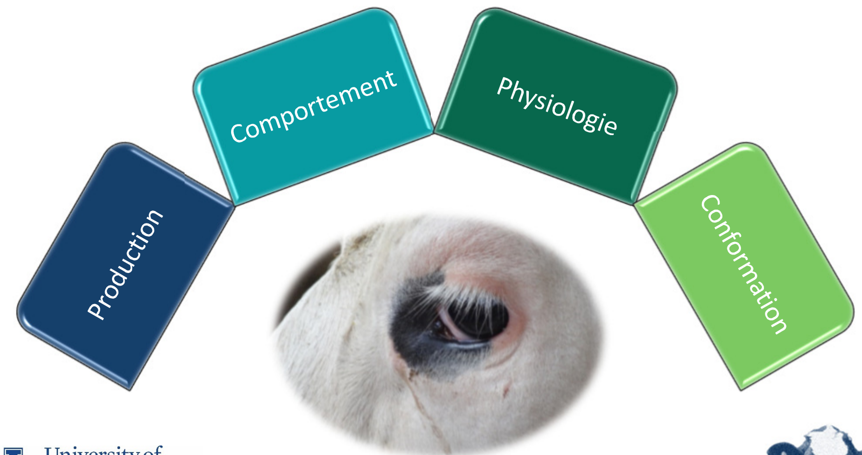
Élevage laitier de précision : défis et opportunités



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ÉLEVAGE LAITIER DE PRÉCISION : APPLICATIONS

- Détection des chaleurs
- Détection de la mammite
- Détection des maladies chez les fraîches vêlées
- Détection des boiteries
- Détection du vêlage
- Caractères génétiques
- Gestion de troupeau

Une seconde « Révolution verte »

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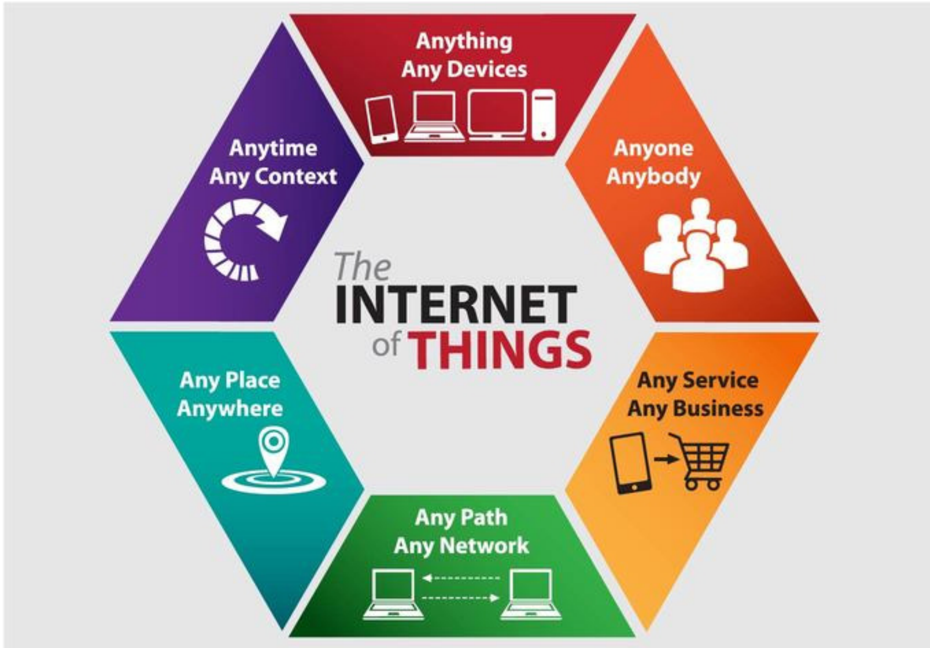
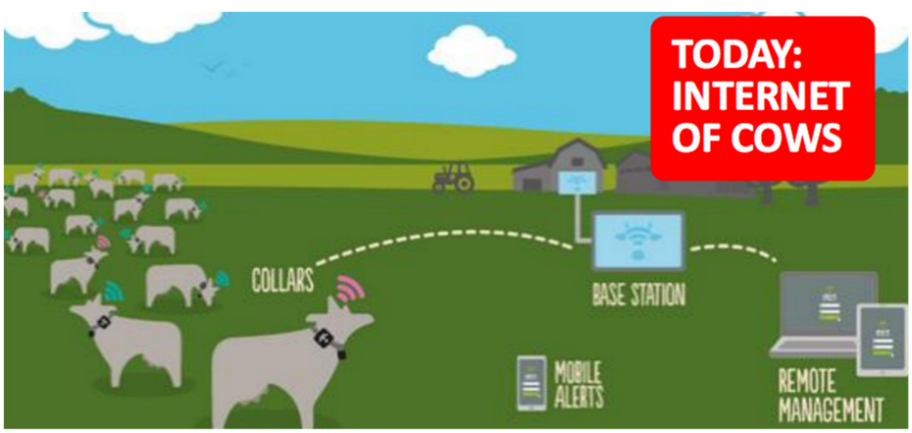
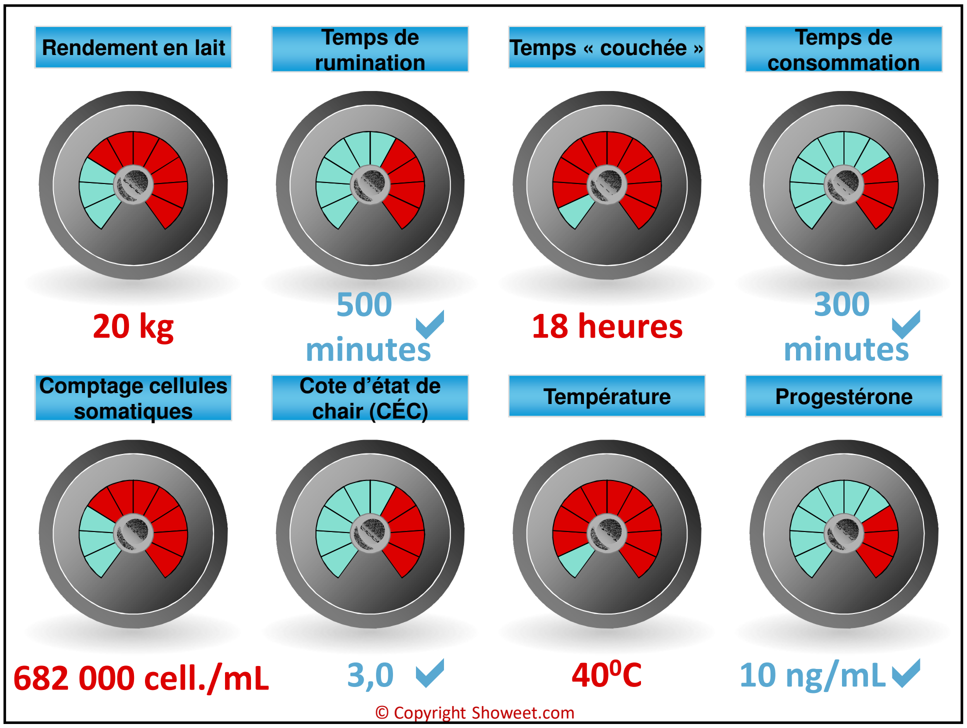
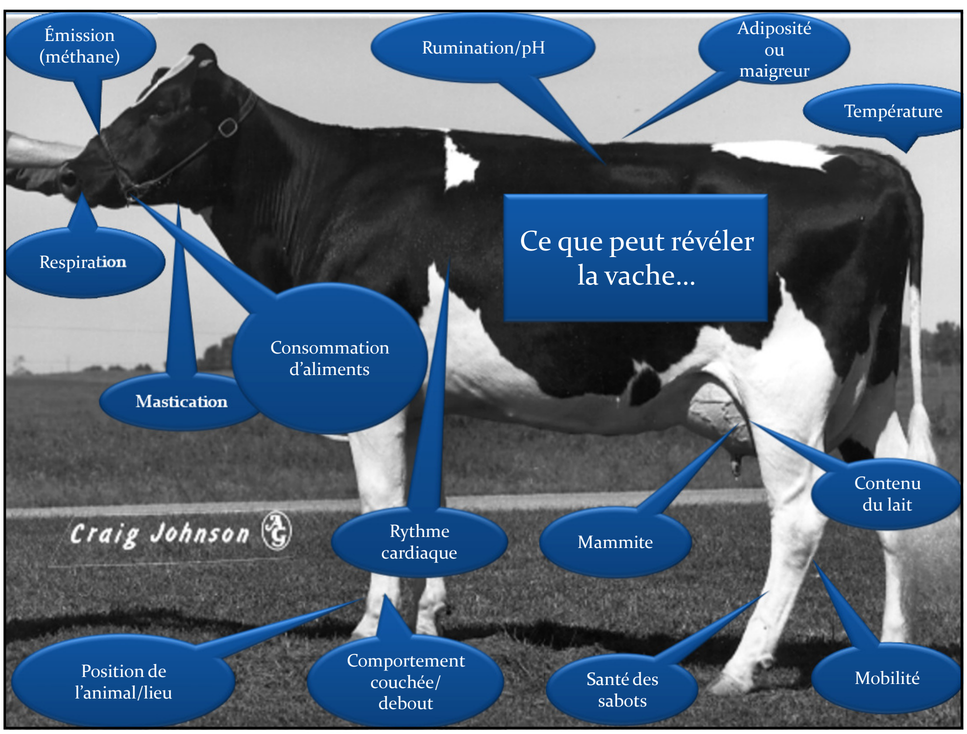

Anything
Any Devices
Anyone
Anybody
Any Service
Any Business
Any Path
Any Network
Any Place
Anywhere
Anytime
Any Context
The INTERNET of THINGS


TODAY:
INTERNET
OF COWS
COLLARS
BASE STATION
MOBILE
ALERTS
REMOTE
MANAGEMENT



Rendement en lait
Temps de rumination
Temps « couchée »
Temps de consommation
20 kg
500 minutes
18 heures
300 minutes
Comptage cellules somatiques
Cote d'état de chair (CÉC)
Température
Progestérone
682 000 cell./mL
3,0
40⁰C
10 ng/mL
© Copyright Showeet.com



Émission (méthane)
Rumination/pH
Adiposité ou maigreur
Température
Respiration
Ce que peut révéler la vache…
Consommation d'aliments
Mastication
Contenu du lait
Craig Johnson
Rythme cardiaque
Mammite
Position de l'animal/lieu
Comportement couchée/ debout
Santé des sabots
Mobilité

Technologie idéale

- Explique un processus biologique sous-jacent
- Peut se traduire en une action concrète
- Rentable
- Flexible, robuste, fiable
- Simple et centrée sur la solution
- Accès facile à l'information

Une foule d'alternatives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College of Agriculture, Food and Environment
Dairy
Precision Dairy
INNOVATIVE TECHNOLOGY
IT STARTS WITH US!


ICEQUBE
GEA
Appareils aux membres

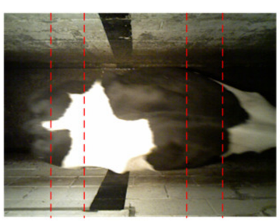

CowManager
EXPERTIS FeverAlert
SMARTBOW
001
10023101001
Appareils sur l'oreille

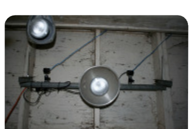

MooMonitor+
Silent Herdsman
SCR by Allflex
Make every cow count
Appareils au cou

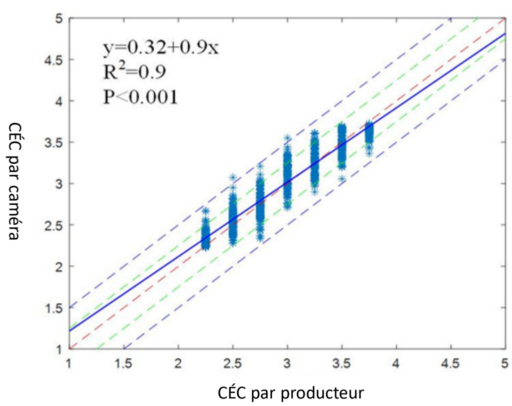

BellaAg
smaXtec
Appareils dans le rumen


Moocall
Medria
Appareils pour le vêlage

Fonctionnement appareil Kentucky (Cote état de chair)







Plus de 99 % des vaches avaient une erreur moyenne absolue de moins de 0,25

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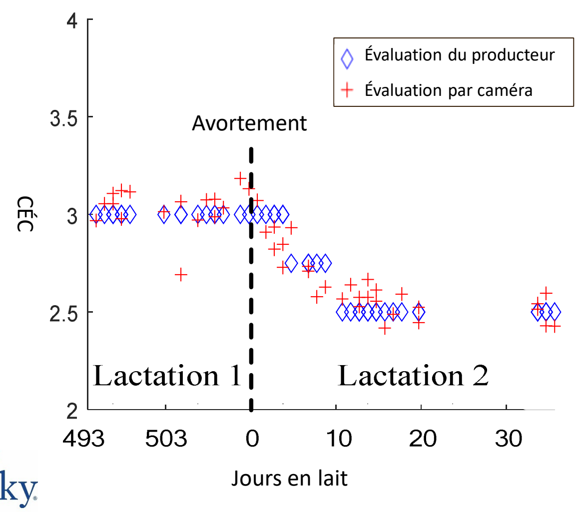
Zhao et coll., 2017

Suivi des changements de CÉC



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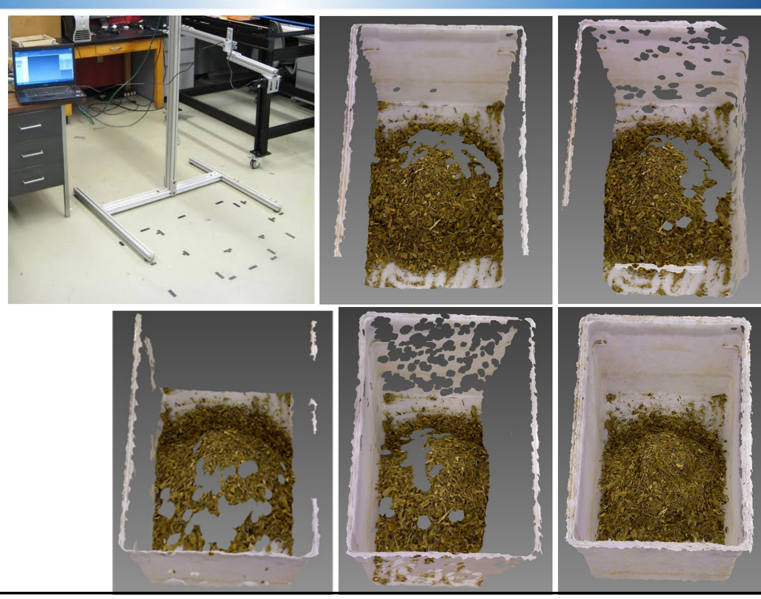
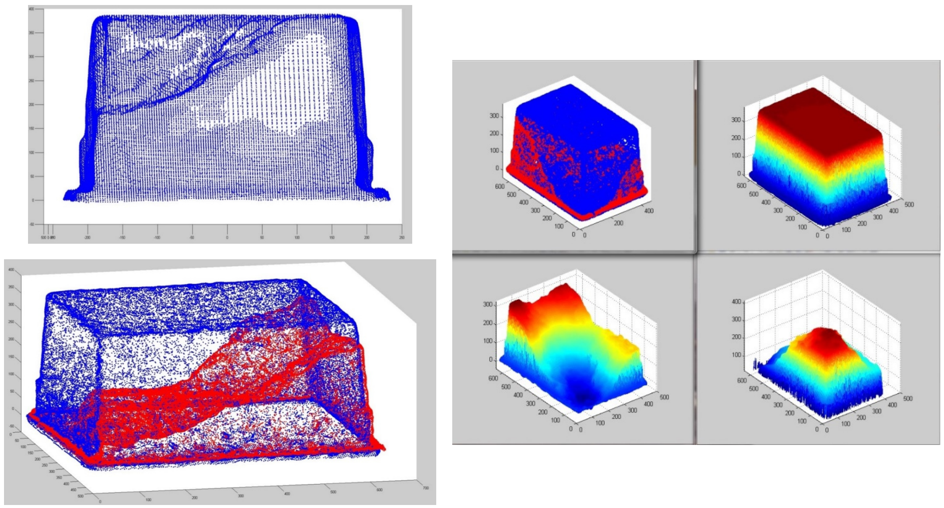
Zhao et coll., 2017

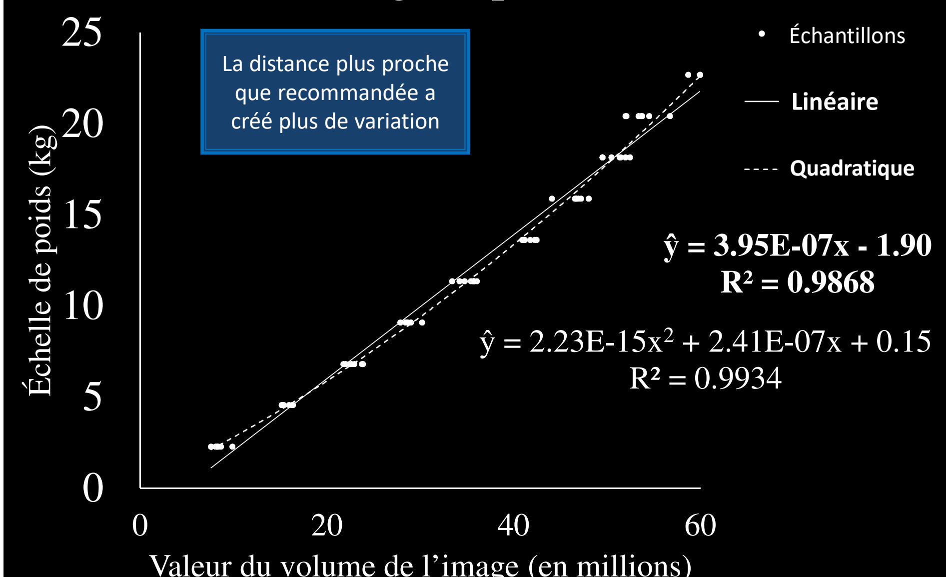
Système d’imagerie

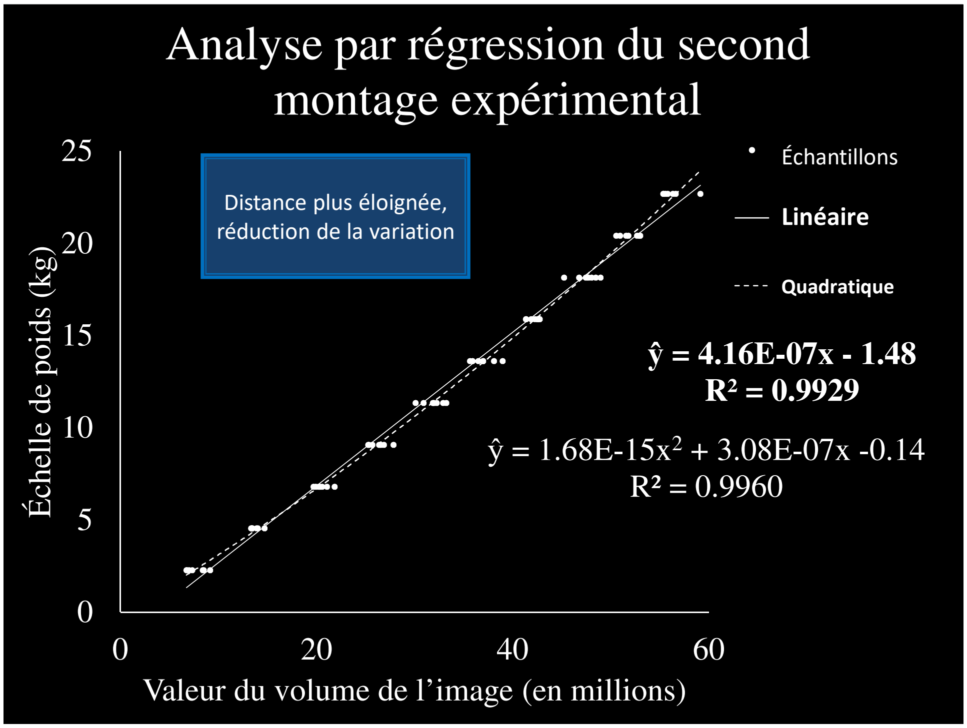


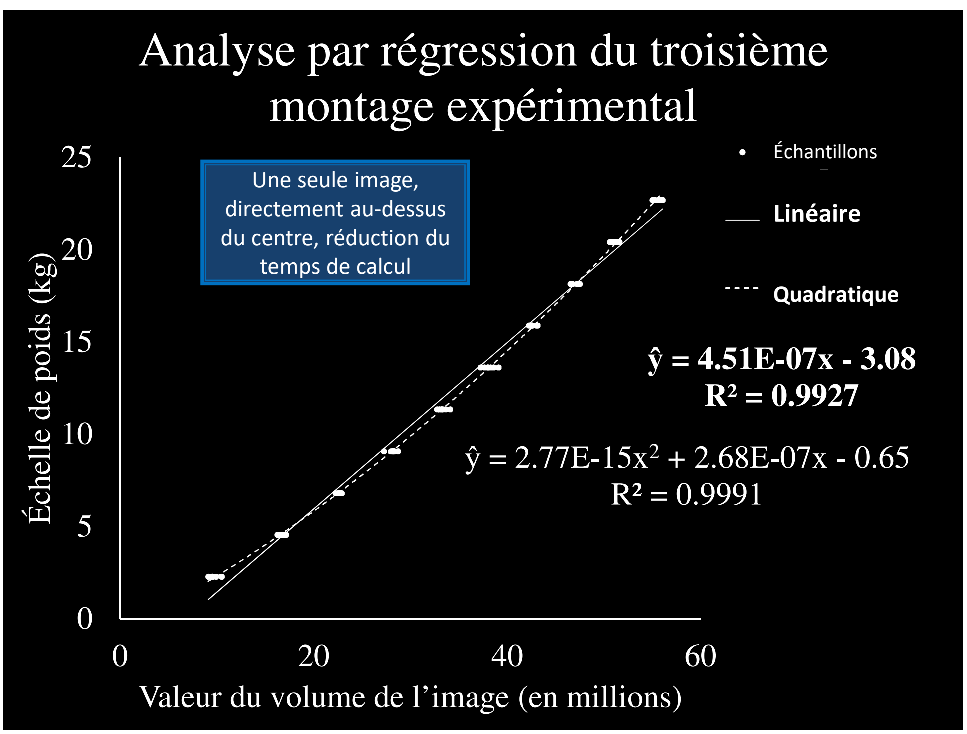
Traitement



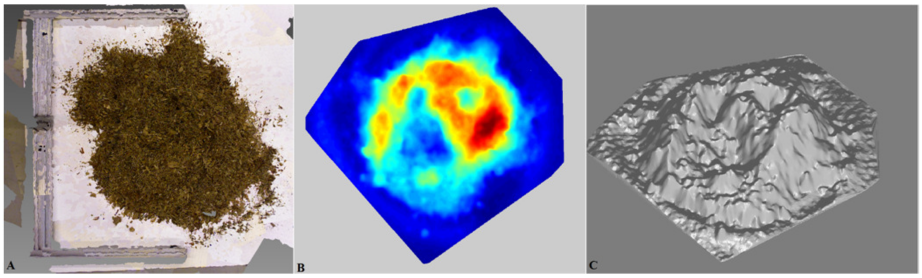
Analyse par régression du premier montage expérimental




Analyse par régression du second montage expérimental
Distance plus éloignée, réduction de la variation
Échantillons
Linéaire
Quadratique
ŷ = 4.16E-07x - 1.48
R² = 0.9929
ŷ = 1.68E-15x² + 3.08E-07x -0.14
R² = 0.9960
Échelle de poids (kg)
Valeur du volume de l'image (en millions)
0
5
10
15
20
25
0
20
40
60


Analyse par régression du troisième montage expérimental
Une seule image, directement au-dessus du centre, réduction du temps de calcul
Échantillons
Linéaire
Quadratique
ŷ = 4.51E-07x - 3.08
R² = 0.9927
ŷ = 2.77E-15x² + 2.68E-07x - 0.65
R² = 0.9991
Échelle de poids (kg)
Valeur du volume de l'image (en millions)
0
5
10
15
20
25
0
20
40
60

Objectifs, pour le futur



- Aliments au sol, sous la caméra
- Les données de profondeur de la surface des aliments différenciées de celles de la profondeur du plancher
- Données de la profondeur obtenues par vue latérale de la profondeur des aliments (surface profilée)
- Multicaméra d’une mangeoire réelle

Comportement sur vidéo

Recherche, Université du Kentucky

Validation de la technologie

Couchée, rumination et consommation

- Technologies :
  - Podomètre AfiAct Plus
  - *CowAlert IceQube*
  - *CowManager Sensoor*
  - *Smartbow*
  - Track *a))) Cow*

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College of Agriculture, Food and Environment

Borchers et coll., 2016

Comportement couchée

Technologie	Nombre de vaches	Corrélation avec les observations visuelles (r)[1]
CowAlert IceQube	48	1,00**
Track a Cow	44	1,00**
Podomètre AfiAct Plus[2]	48	1,00**

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Borchers et coll., 2016

Comportement à la mangeoire

Technologie	Nombre de vaches	Corrélation avec les observations visuelles (r)[1]
CowManager Sensoor	[illegible]	0,87**
Track a Cow	41	0,93**

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Borchers et coll., 2016

Temps de rumination

Technologie	Nombre de vaches	Corrélation avec les observations visuelles (r)[1]
CowManager Sensoor	46	0,69**
Smartbow	46	0,96**

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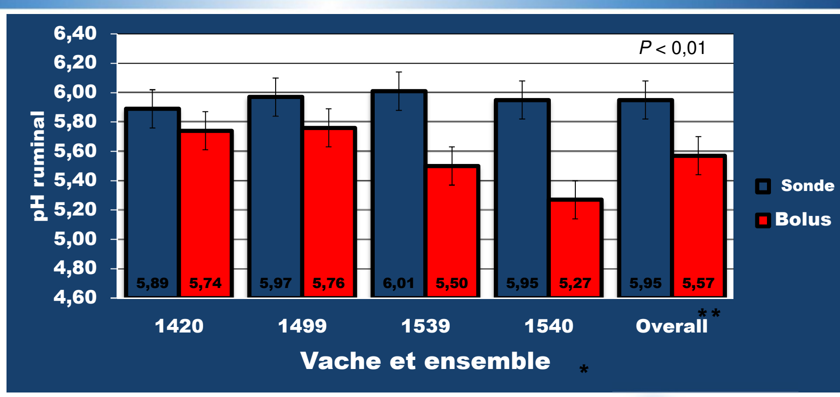
Borchers et coll., 2016

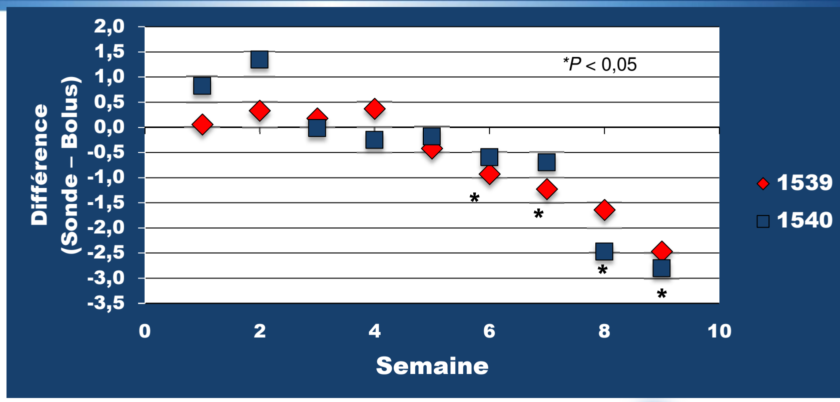
Validation du pH ruminal



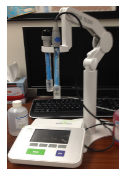
De façon significative, le pH ruminal mesuré par le bolus était constamment plus élevé, que celui mesuré par un appareil de laboratoire.

Weatherly et coll., 2014

Déviation du pH ruminal

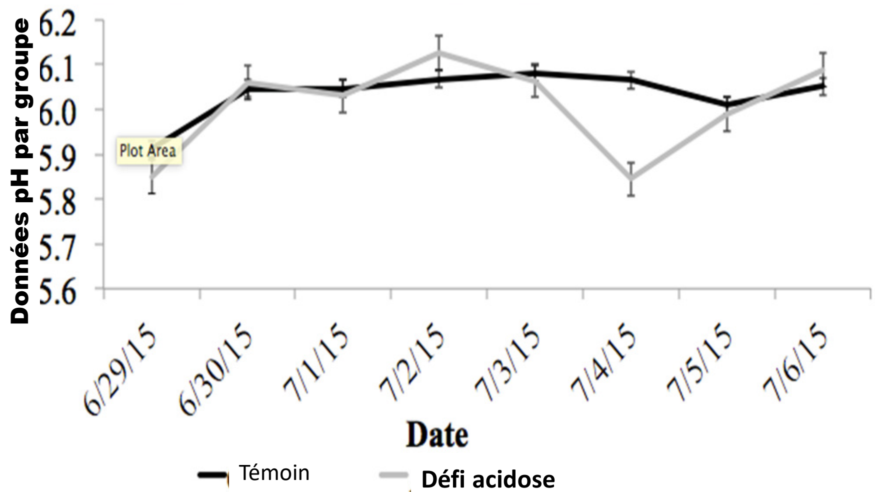


Le pH ruminal obtenu des deux techniques n'était pas différent jusqu'à la sixième semaine, puis le pH du bolus a commencé à dévier.



Weatherly et coll., 2014

Défi pH-Smaxtec



Skelton et coll., 2016

Recherche Université du Kentucky

Détection hâtive de la maladie

Détection plus hâtive de la maladie par rapport à l'observation visuelle seule

Amélioration des résultats du traitement individuel de la vache

Indique un problème plus grand, à l'échelle du troupeau, mène à une amélioration des stratégies de prévention

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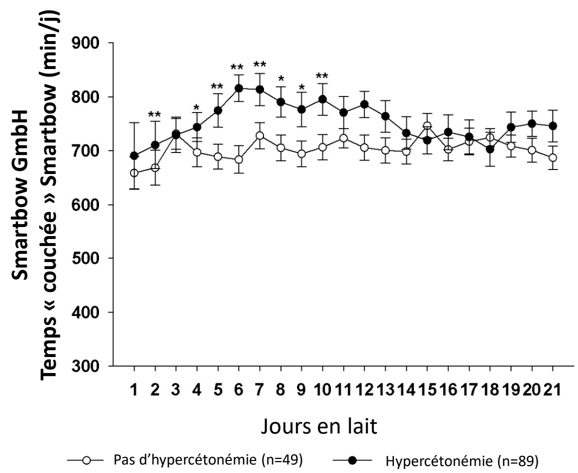
College of Agriculture, Food and Environment

Hypercétonémie : Vache couchée plus longtemps



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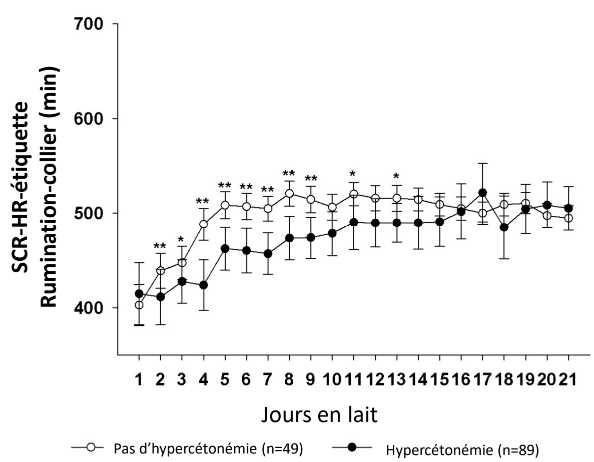
Tsai et coll. 2016, non publié

Hypercétonémie : Augmentation du temps de rumination



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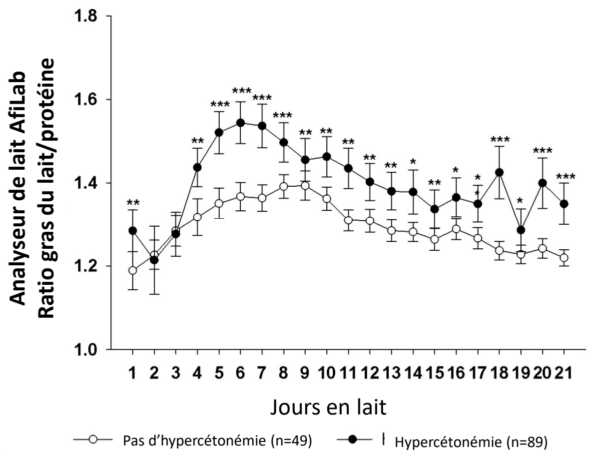
Hypercétonémie :
Ratio gras/protéine plus élevé



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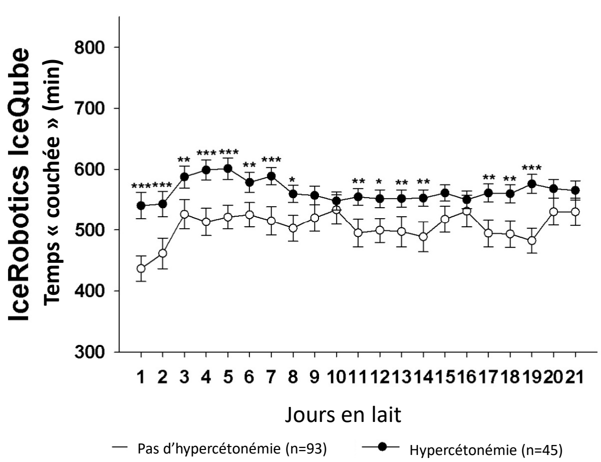
Hypocalcémie :
Vache couchée plus longtemps



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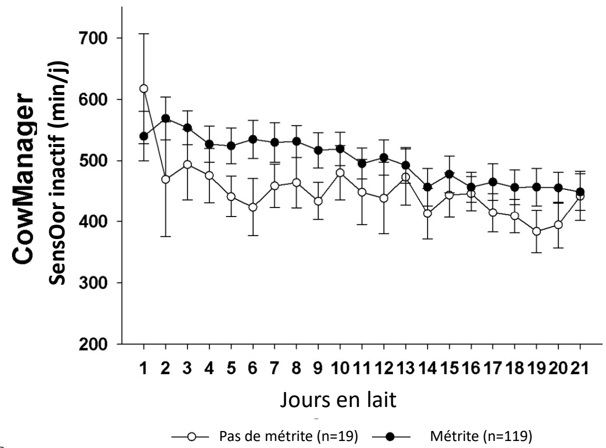
Métrite :
Vache couchée plus longtemps



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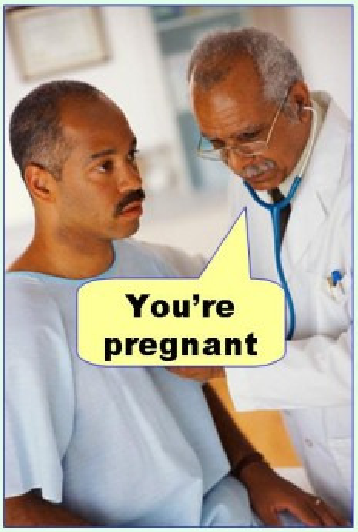
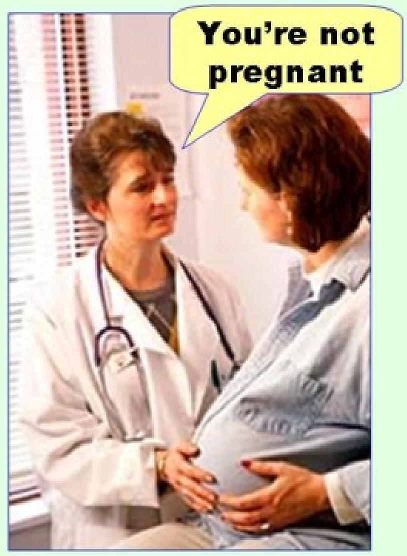
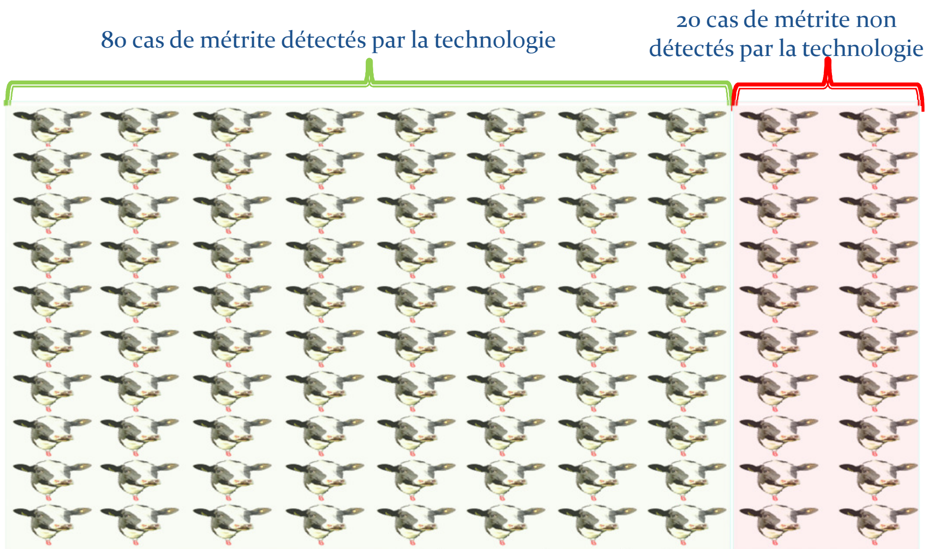
Type I error
(false positive)



Type II error
(false negative)

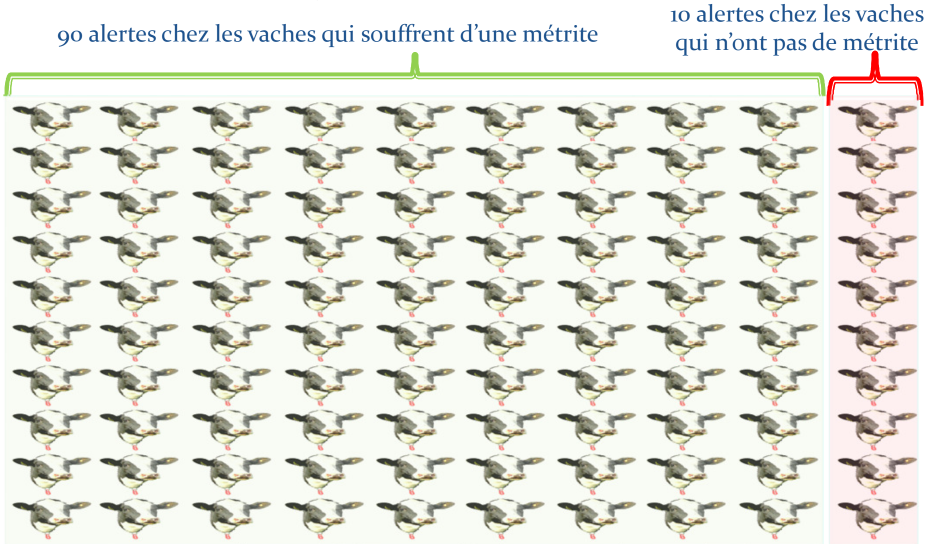


Combien des vaches affectées d'une métrite découvrons-nous ?



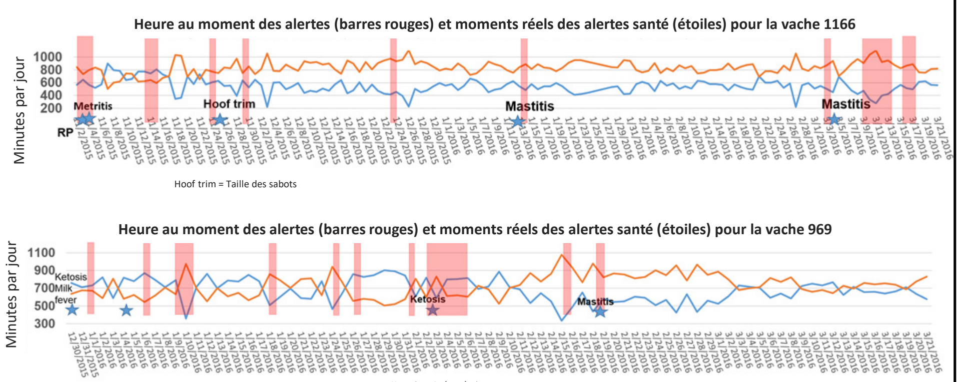
Exemple : 100 cas de métrite

Combien d'alertes correspondent à un cas réel ?



Exemple : 100 cas d'alertes de métrite

Moment de l'alerte/comparaisons avec la réalité



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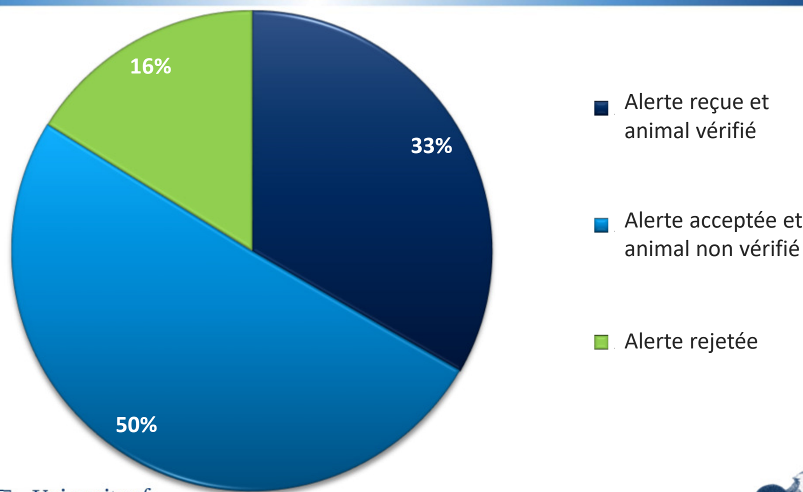
Eckelkamp et coll., 2017

Réaction du producteur aux alertes données par l'appareil



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Résumé de l'état de santé des vaches soumises aux vérifications intensives du 1er au 14e JEL

Variable	Acétonémie sous-clinique	Hypocalcémie	Métrite clinique	Pas de maladie
Nb vaches diagnost., en vache jours	208	176	30	-
Temps moyen rumination ± ÉT (h/j)	5,49 ± 1,93	5,20 et 1,77	5,25 et 2,21	6,08 et 1,90
Température moyenne réticulo-rumen ± ÉT (°C)	39,04 ± 1,16	38,99 ± 0,59	39,36 ± 0,56	39,05 ± 1,26
Temps moyen « couchée » ± ÉT (h/j)	10,37 ± 3,43	10,33 ± 3,94	11,41 ± 3,11	9,51 ± 3,13
Prod. moyenne lait ± ÉT (kg/j)	27,60 ± 8,20	25,09 ± 8,67	25,45 ± 10,65	28,92 ± 7,39

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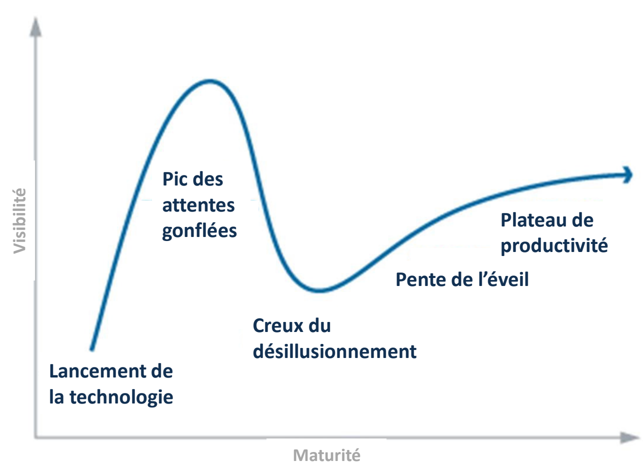
Stone et coll. 2016, non publié

Sensibilité et spécificité du temps de rumination, de l'activité, de la température du réticulo-rumen, du temps « couchée » et des périodes de temps « couchée » pour chaque maladie, selon différents seuils d'alerte pour détecter la maladie

Maladie	Sensibilité (%)	Spécificité (%)	Précision
Acétonémie sous-clinique	98	6	94
	55	91	57
Hypocalcémie	97	8	55
	85	22	55
Métrite clinique	86	52	86
	67	85	67

Stone et coll. 2016, non publié

Cycle de vie d'un produit selon Gartner



De combien d'information avons-nous réellement besoin ?

Accordons-nous trop d'importance à la détection de la maladie ?

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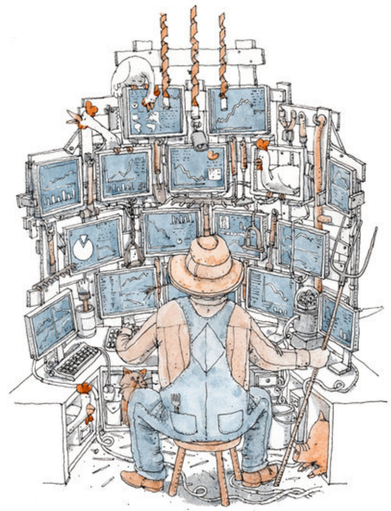
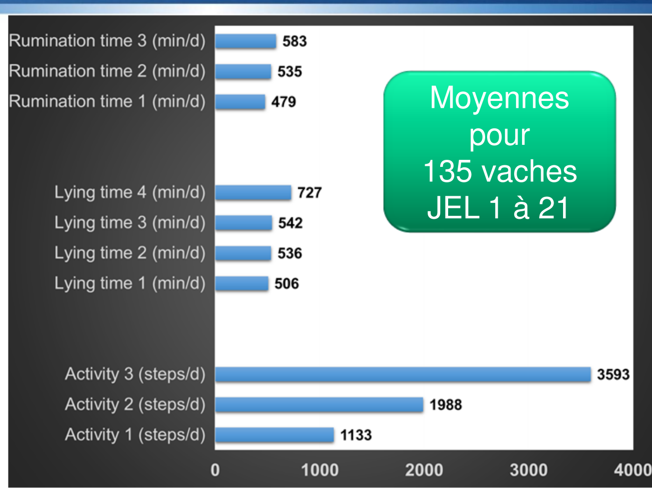
Intégration des données



Pour comprendre l'aspect économique des technologies

Les ratons laveurs raffolent des fils de catégorie 5

X ≠ X et Y ≠ Y



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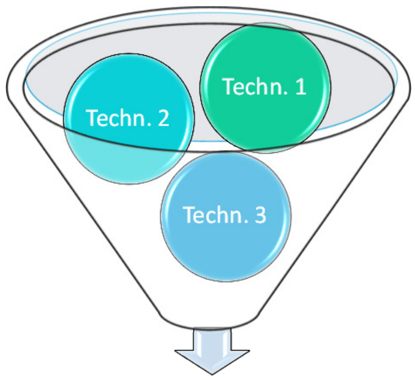
Des données disparaissent



847 vaches-jours (29 %) sur un total possible de 2 898

- 138 vaches
- JEL 1 à 21
- 2 898 vaches-jours
- 7 technologies

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Autres avertissements

- Une immense variation entre les vaches et entre les troupeaux
- Plusieurs facteurs de régie et plusieurs conditions environnementales affectent ces variables
- Parfois, au hasard, certaines étiquettes cessent d'émettre
- Le positionnement des étiquettes est important
- Les changements de groupes et de parcs influencent les comportements
- Certaines vaches boudent les règles
- Tous les changements ne sont pas linéaires

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Six questions que les producteurs devraient poser

1. Quelle est la sensibilité/la spécificité de la condition qui nous intéresse ?

2. Par année, quel pourcentage des appareils brisent ?

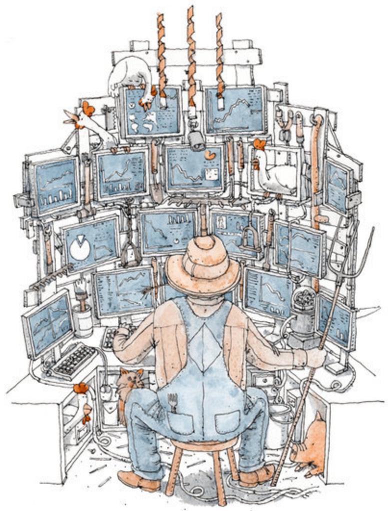
3. Quelle est la politique de la garantie ?

4. Quelles sont les conditions du passage à une nouvelle version des appareils ?

5. Quels sont les coûts totaux (logiciels, appareils, entretien, stockage des données) ?

6. Quels sont les protocoles disponibles pour agir en cas d'alerte ?

1. Intégration des données



2. Comprendre l'aspect économique des technologies

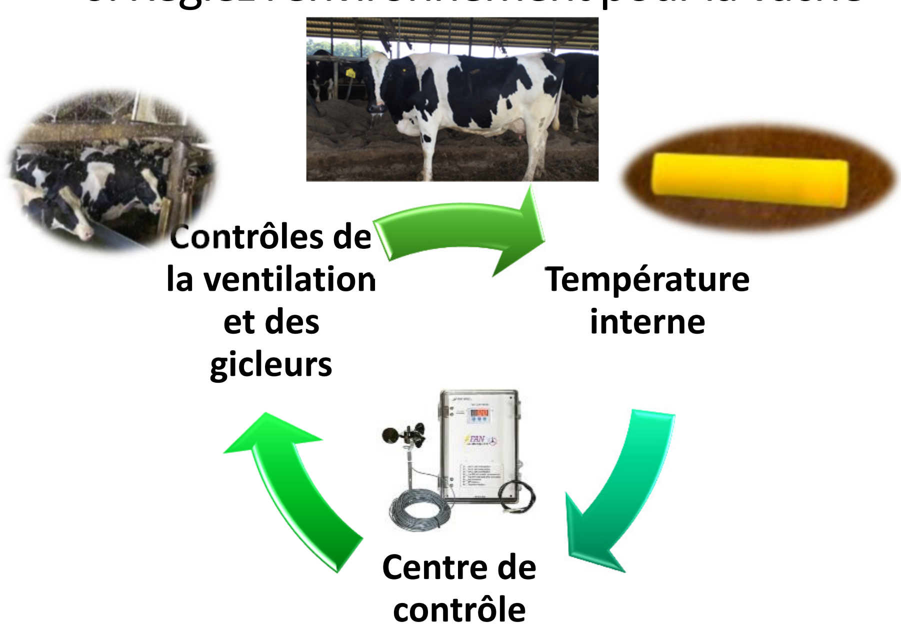
3.

4. Groupes de producteurs-utilisateurs

5. Données par groupe ou par troupeau

- Plus utiles pour les changements à l'intérieur du groupe ou à l'intérieur du troupeau
- Peut être utile pour comparer différentes cohortes
- Gardez en tête la variation naturelle et le décalage
- Soyez extrêmement prudent lors de comparaisons entre les troupeaux
- Remettez en question ce qui relève de « la sagesse populaire »

6. Réglez l'environnement pour la vache



7. Surveillance des veaux

- Données d'alimentation du veau
- Ce qu'il peut porter
- Physiologie ?

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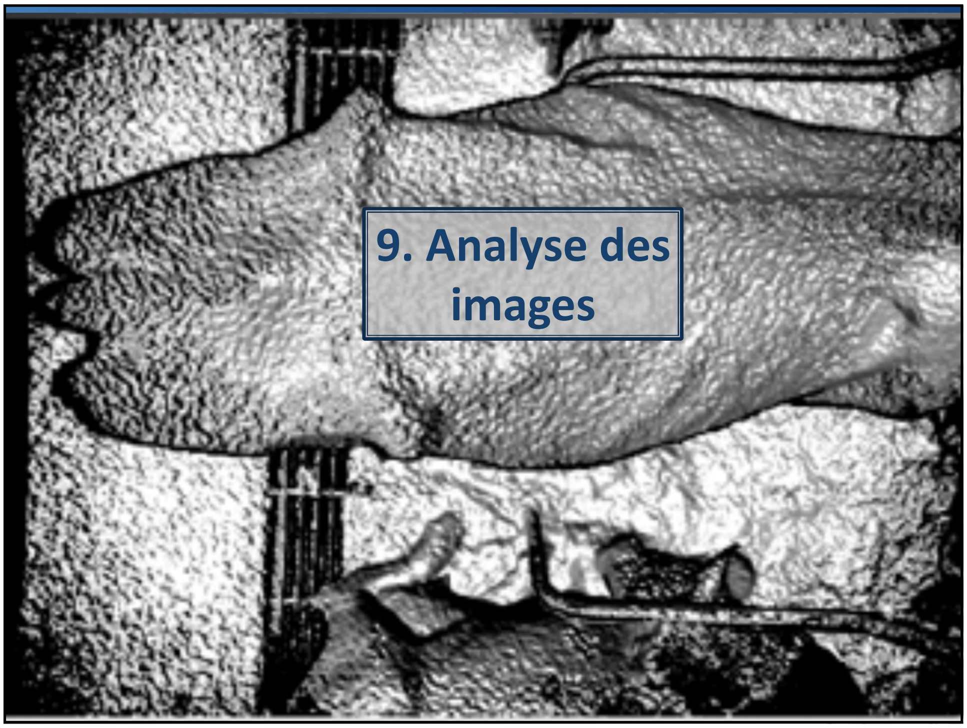
8. Évaluations génétiques

- Peut fournir de l'information non disponible auparavant pour les évaluations génétiques
- Caractères nouveaux ou améliorés (prise alimentaire, boiterie, CÉC, tolérance à la chaleur, fertilité)
- Amélioration de la précision des données (rendement en lait, en gras, en protéine, CCS, caractères liés à la santé)
- Synergies avec la génomique


9. Analyse des images


10. La puissance du lait

Questions ?

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