Stochastic systems model assessment of historical cow-calf biological and economic efficiency for different mature cow weight and peak lactation combinations in the Kansas Flint Hills

by

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B.S., Kansas State University, 2014
M.S., Kansas State University, 2017

AN ABSTRACT OF A DISSERTATION

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Department of Diagnostic Medicine/Pathobiology
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Abstract

A stochastic, individual based systems simulation model describing U.S. beef cow-calf production was developed. Accounting for genetics, nutrition, reproduction, growth, health, and economics, allows analysis of various scenario outcomes encompassing different genetic, management, and marketing strategies. The model's stochastic nature enables consideration of biological variation and probabilistic risk, while the systems design accounts for time delays and complex, prolonged feedback structure, all inherent to beef production. Any number of production years and iterations can be simulated. These capabilities make it ideal for decision analysis and assessment of long-run outcomes regarding a multitude of metrics simultaneously.

Parameterizing the model to match Kansas Flint Hills production and economic conditions for the years 1995 through 2018, 32 breeding systems with different genetic combinations for mature cow weight and peak lactation potential were simulated 100 iterations each. Sire mature cow weight genetics ranged from 454 kg to 771 kg in 45 to 46 kg increments. Sire peak lactation genetics were considered at 6.8, 9, 11.3, and 13.6 kg/d for all eight mature cow weights. Retaining replacement females, the breeding herd size goal was 100 animals. Model decision rules aimed to meet individual animal nutrient requirements.

Utilizing model results for the years 2000-2018, three different validation procedures were applied. A six person panel with combined expertise spanning veterinary medicine, animal breeding and genetics, ruminant nutrition, agricultural economics, and beef production modeling reviewed model output in both absolute and comparative scenario terms. Separately, raw model results were assessed against actual historical cow-calf production

data. Finally, exploratory factor analysis was applied to interpret the underlying factor scores of model output relative to real-world cow-calf production data.

In cow-calf production, biological and economic efficiency are not perfectly synonymous. Research simultaneously assessing both the biological and economic efficiency of different mature cow weight and peak lactation combinations for twenty-first century cow-calf production is scarce to non-existent. Aggregating simulation results for the 2000 through 2018 production years, under the specific parameters previously described, larger, heavier milking cows exceled in kilograms weaned per cow exposed, while kilograms weaned per net energy for maintenance (kg/Mcal*100) favored smaller, heavier milking cows. Assuming no price differentiation between weaned calves from different breeding systems, 454 and 499 kg mature cow weight with 13.6 kg/d peak lactation had the highest median annual enterprise return on investment (fed ration, pasture, replacement, and interest expenses) at 8.9 and 7.4 percent, respectively. Applying the assumptions that herds comprised of 454 and 499 kg mature cow weight with 13.6 kg/d peak lactation do not exist and that all weaned calves from 454 kg mature cow weight breeding systems receive a small frame price discount, the 544 kg mature cow weight-13.6 kg/d peak lactation combination generated the greatest median annual return on investment at 7.0 percent. Several combinations of 499, 544, 590, and 635 kg mature cow weights with 11.3 or 13.6 kg/d peak lactation produced a median annual return on investment between 4.1 percent and 5.4 percent.

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Chapter 1 - Literature Review and Opportunities

Systems Modeling

In 2019, the National Academies of Sciences, Engineering, and Medicine identified advancement of multi-disciplinary systems approaches as the number one priority in order to generate critical food and agriculture breakthroughs by 2030 (NASEM, 2019). Holistic solutions to agriculture's greatest challenges will only be discovered if the scientific community relegates single-discipline approaches in favor of quantitative models that "more methodically integrate science, technology, human behavior, economics and policy" (NASEM, 2019).

Concepts

Hirooka (2010) defines a model as "a simplified and idealized mathematical representation of reality based on an ordered set of assumptions and observations." The time delays, the complex and prolonged feedback structure, and the significant capitalization inherent to the beef industry prohibit many long-term or large scale studies. By integrating the literature from past research and knowledge from numerous specialized fields, modeling enables enhanced understanding in a time-efficient and cost-effective manner, not only by capitalizing on past discoveries, but by identifying research gaps. Furthermore, Shafer et al. (2007) demonstrated that beef production's natural biological variation often calls for stochastic modeling features, which can be difficult to replicate in the real world due to the previously discussed constraints.

Systems thinking focuses on the interpretation of how different components of a system interact with one another and how an action or change in one component affects the entire system, either directly or through potential feedback structures (Sterman, 2000). Systems modeling combines systems thinking with mathematical modeling to create tools for learning about complex systems (Sterman, 2000). Past and present systems modeling applications span many fields of study including, but not limited to, manufacturing, business management, investment strategy, government policy, environmental management, and epidemiology (Sterman, 2000). While the particular goal and scope of each study is case specific, several underlying principles remain constant.

The nature of systems modeling often demands multidisciplinary expertise and cooperation. A multidisciplinary approach can identify emergent properties (Ebersohn, 1976; Fischer, 2008), which result from allowing narrow, discipline-specific conclusions or knowledge to interact within a complex system. Such emergent properties are ideal for understanding how a new discovery or alternate practice fit into the broader system. Even the practice of systems modeling generates important feedback structures in research and innovation. Single-discipline, physical experiments often provide the inputs and grounding for systems modeling, while modeling helps identify: (1) knowledge gaps where further experimentation or data collection is warranted, and (2) the true contribution of new discoveries or novel strategies to a broader system.

More recently, advances in computing power have allowed systems modelers to better understand and implement stochastic processes and agent (individual) based modeling. Thus, risk and uncertainty evaluation have become major components of systems modeling. Proper systems modeling mathematically integrates the complex component interactions and feedback structure within a specified scope of a given production system and allows the flexibility to employ stochastic elements.

Beef Cattle Production Modeling History

Modeling is not a novel idea to beef production science. Over the decades, many researchers have developed systems based models to assess a multitude of complex beef production questions (Hirooka, 2010) ranging from specific biological traits such as growth curves (Richards, 1959) to broader topics related to production system bio-economics (Davis et al., 1994) and life-cycle assessments of environmental impacts (Asem-Hiablie et al., 2019).

Ruminant nutrition has received particular attention in modeling application. Tedeschi and Fox (2014) summarizes the evolution of computer-based ruminant nutrition modeling in the form of decision support systems through the development and application of models such as the Cornell Net Carbohydrate and Protein System (CNCPS) (Fox et al., 2004) and the Cornell Value Discovery System (Tedeschi et al., 2004). Researchers at the US Meat Animal Research Center also developed a model for assessing the nutrient demands of maintenance and growth, the Decision Evaluator for the Cattle Industry (DECI) (Williams and Jenkins, 2003a,b,c). The utilization of such models has greatly enhanced industry understanding in ration design and nutrition programs at multiple cattle development stages.

While most nutrition focused simulation models have been aimed at assessing energy demands and energy efficiency, the breeding and genetics field has illustrated the use of simulation modeling and sensitivity analysis to determine the relative economic value of varying phenotypic and genetic traits (MacNeil et al., 1994; MacNeil et al., 1997). The selection indices resulting from such techniques have become staple tools in today’s genetic selection methods.

One of the most advanced beef production models is the Colorado Beef Cattle Production Model (CBCPM) (Bourdon and Brinks, 1987; Shafer et al., 2005), an adaptation of the foundational TAMU model (Sanders and Cartwright, 1979; Kahn and Spedding, 1983). CPCPM is a broad-scope, whole herd model that accounts for both genetics and nutrition in combination with forage production and economics.

Verification and Validation

Verification establishes that a model performs conceptually and mathematically as intended by the modeler; whereas validation assesses how accurately a model characterizes reality (Thacker et al., 2004). Verification and validation take different forms at different model development stages and should be performed throughout the modeling process (Barlas, 1996). Validation definition varies with model type and intended use; however, it should include both qualitative and quantitative elements (Barlas, 1996). Often, model development is motivated by a shortage of real-world data describing the scope of interest in a particular system. Coupling data scarcity with the ambiguity of appropriate methodology, quantitative validation has chronically challenged modelers (Barlas, 1996).

As described by Shafer et al. (2005), quality long-run datasets with whole system parameters defined may be impossible to come by in the beef industry. For a short duration, Villalba et al. (2006) controlled real-world environment and management as closely as possible to match model parameters and then compared between real and simulated data to establish model validity. Unfortunately, there was no ability to assess long-run feedback structures and compounding of differences. If sufficient real data are not available, Barlas (1989) suggests applying long-term pattern evaluation using autocorrelation and cross-correlation to help establish long-run pattern validity using data generated with different random seeds.

Villalba et al. (2006) did not go so far as to perform any stringent hypothesis testing. Many have demonstrated the flaws in applying inferential statistics to computer simulated data (Hofmann et al., 2018). Even if one explored inferential methods, Harrison (1990) clearly demonstrates that any statistical analysis involving a simulation model is highly subject to the number of iterations and that "failing to reject" a null hypothesis of model equality does little to confirm validity. Model validation is a logical concept, but when put into practice it is impossible to validate any model with complete certainty.

Sensitivity analysis, often part of model validation, refers to multiple qualitative and quantitative methodologies aimed at evaluating model output response to alternative model parameters (Frey and Patil, 2002; Ioos and Lemaitre, 2015; Trucano et al., 2006; Walker and Fox-Rushby, 2001). Xiao et al. (2017) describes principal component analysis (PCA) methods to address multivariate output sensitivity analysis in complex models.

An ostensibly similar data dimension reduction technique to PCA, but with a different fundamental interpretation, exploratory factor analysis (EFA) has been widely applied to psychology, sociology, and communication fields (Park et al., 2002). EFA interprets multivariate patterns and interrelationships by estimating an underlying, unobservable (latent) factor structure that influences observed data values (Luo et al., 2019; Park et al., 2002). Whereas PCA utilizes total variation among variables without consideration for its source, EFA separates variable variation into common variance and unique variance (Park et al., 2002). For each measured variable, common variance represents the variance explained by one or more latent factors, whereas unique variance stems from other sources, including measurement error (Luo et al., 2019; Park et al., 2002).

Future Opportunities

Despite the long, but incomplete list of modeling benefits already described, systems modeling's application to the beef industry, and agriculture in general, is far from its potential. NASEM (2019) identified three primary goals for food and agriculture to achieve by 2030: "(1) improving the efficiency of food and agricultural systems, (2) increasing the sustainability of agriculture, and (3) increasing the resiliency of agricultural systems to adapt to rapid changes and extreme conditions." For reasons already discussed, NASEM (2019) strongly recommends prioritizing multi-disciplinary, systems techniques to achieve the outlined goals.

As continued research enhances the understanding of beef production and additional production data is gathered, there is continuous need for updates and improvements to past models and their derivative equations (Hirooka, 2010). This process often stems from the inherent feedback loop in the modeling process where model building identifies research and data gaps, as well as research areas with the greatest impact potential. Once advancements in a specific field have been achieved, the key becomes determining their true impact and the optimal way to fit those advancements into the broader system. There are several more reasons to recreate or update beef production models. Growing computing power creates the possibility for more model complexity without sacrificing computing time. In addition, building models in more modern, open-source programming languages encourages application. Perhaps most importantly, model building provides the modelers with synthesized learning about how an entire system functions.

Over the years, lack of wide-spread understanding in modeling techniques and difficulty in model validation have likely limited the trust in many systems models to the model developers alone. Furthermore, as the multidisciplinary groups often required to build effective systems models disband or progress in career paths, their models tend to fall into disuse. Models without extensive documentation, updated programming language, or with extreme complexity often succumb to such a fate. Even as far back as Penning De Vries (1977) there were concerns regarding the tradeoffs between model complexity and usefulness: “Good scientific models are often too detailed or too speculative for those who want to apply them, whilst models used for predictive or management purposes are often too trivial or too crude to challenge scientific interest.” Developing believable models and prioritizing the ability to pass such models to the next generation of model users is critical in realizing full modeling potential.

Enhanced understanding of the sustainability connection between agricultural practices, the natural environment, economic well-being, and human society demands a paradigm shift from output maximization to system optimization. Furthermore, whole system optimization and efficiency must be assessed from multiple dimensions. Moving forward successful agricultural operations will balance biological resource efficiency with economic efficiency, environmental impact, and social demands. Such a paradigm shift requires measuring and understanding the tradeoffs between various goals, strategies, and practices. Systems modeling provides the opportunity to assess such tradeoffs and multidimensional optimization strategies required to make the next major advancements in agricultural production.

Research Objective

The objective of the present research was to develop a stochastic systems simulation model of cow-calf production based on individual animals with daily time steps and capable of accounting for the relevant nutrition, reproduction, genetics, health, and economic conditions of a single enterprise or generalized industry setting. In particular, the model emphasized the ability to simultaneously analyze a production system from multiple angles. In its present state, the model is capable of assessing both biological and economic efficiency at the cow-calf level across any number of years. The model was designed to allow for future expansion into the entire beef production system and for the integration of additional metrics related to environmental sustainability.

In order to facilitate future model application, the model was written in the open source programming language, R (R Core Team, 2019). Specific attention was also paid to verification and validation procedures, through comparison to real world data and techniques such as EFA (Park et al., 2002), to build model confidence and believability.

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Chapter 2 - Stochastic, individual-based systems model of beef cow-calf production: model development and validation

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Abstract

A stochastic, individual based systems simulation model describing U.S. beef cow-calf production was developed. Accounting for genetics, nutrition, reproduction, growth, health, and economics, allows analysis of various scenario outcomes encompassing different genetic, management, and marketing strategies. The model's stochastic nature enables consideration of biological variation and probabilistic risk, while the systems design accounts for time delays and complex, prolonged feedback structure, all inherent to beef production. Any number of production years and iterations can be simulated. These capabilities make it ideal for decision analysis and assessment of long-run outcomes regarding a multitude of metrics simultaneously.

Parameterizing the model to match Kansas Flint Hills production conditions for the years 1995 through 2018, 32 breeding systems with different genetic combinations for mature cow weight and peak lactation potential were simulated 100 iterations each. Sire mature cow weight genetics ranged from 454 kg to 771 kg in 45 to 46 kg increments. Sire peak lactation genetics were considered at 6.8, 9, 11.3, and 13.6 kg/d for all eight mature cow weights. Retaining replacement females, the breeding herd size goal was 100 animals. Model decision rules aimed to meet individual animal nutrient requirements. The years 1995 through 1999 were considered burn-in years for initial exogenous parameters.

Utilizing model results for the years 2000-2018, three different validation procedures were applied. A six person panel with combined expertise spanning veterinary medicine, animal breeding and genetics, ruminant nutrition, agricultural economics, and beef production modeling reviewed model output in both absolute and comparative scenario terms. Separately, raw model results were assessed against actual historical cow-calf production data. Finally, exploratory factor analysis was applied to interpret the underlying factor scores of model output relative to real-world cow-calf production data.

Introduction

Systems Modeling

In 2019, the National Academies of Sciences, Engineering, and Medicine identified advancement of multi-disciplinary systems approaches as the number one priority in order to generate critical food and agriculture breakthroughs by 2030 (NASEM, 2019). Holistic solutions to agriculture's greatest challenges will only be discovered if the scientific community relegates single-discipline approaches in favor of quantitative models that "more methodically integrate science, technology, human behavior, economics and policy" (NASEM, 2019).

History

Hirooka (2010) defines a model as "a simplified and idealized mathematical representation of reality based on an ordered set of assumptions and observations." The time delays, the complex and prolonged feedback structure, and the significant capitalization inherent to the beef industry prohibit many long-term or large scale studies. By integrating the literature from past research and knowledge from numerous specialized fields, modeling enables enhanced understanding in a time-efficient and cost-effective manner, not only by capitalizing on past discoveries, but by identifying research gaps. Furthermore, Shafer et al. (2007) demonstrated that beef production's natural biological variation often calls for stochastic modeling features, which can be difficult to replicate in the real world due to the previously discussed constraints.

Systems thinking focuses on the interpretation of how different components of a system interact with one another and how an action or change in one component affects the entire system, either directly or through potential feedback structures (Sterman, 2000). Systems modeling combines systems thinking with mathematical modeling to create tools for learning about complex systems (Sterman, 2000). Past and present systems modeling applications span many fields of study including, but not limited to, manufacturing, business management, investment strategy, government policy, environmental management, and epidemiology (Sterman, 2000). While the particular goal and scope of each study is case specific, several underlying principles remain constant.

The nature of systems modeling often demands multidisciplinary expertise and cooperation. A multidisciplinary approach can identify emergent properties (Ebersohn, 1976; Fischer, 2008), which result from allowing narrow, discipline-specific conclusions or knowledge to interact within a complex system. Such emergent properties are ideal for understanding how a new discovery or alternate practice fit into the broader system. Even the practice of systems modeling generates important feedback structures in research and innovation. Single-discipline, physical experiments often provide the inputs and grounding for systems modeling, while modeling helps identify: (1) knowledge gaps where further experimentation or data collection is warranted, and (2) the true contribution of new discoveries or novel strategies to a broader system.

More recently, advances in computing power have allowed systems modelers to better understand and implement stochastic processes and agent (individual) based modeling. Thus, risk and uncertainty evaluation have become major components of systems modeling. Proper systems modeling mathematically integrates the complex component interactions and feedback structure within a specified scope of a given production system and allows the flexibility to employ stochastic elements.

Over the decades, many researchers have developed systems based models to assess a multitude of complex beef production questions (Hirooka, 2010) ranging from specific biological traits such as growth curves (Richards, 1959) to broader topics related to production system bio-economics (Davis et al., 1994) and life-cycle assessments of environmental impacts (Asem-Hiablie et al., 2019). Two of the most advanced and frequently cited beef production models are the TAMU model (Sanders and Cartwright, 1979; Kahn and Spedding, 1983) and an adaptation of the TAMU model, the Colorado Beef Cattle Production Model (CBCPM) (Bourdon and Brinks, 1987; Shafer et al., 2005).

Future Opportunities

Despite the long, but incomplete list of modeling benefits already described, systems modeling's application to the beef industry, and agriculture in general, is far from its potential. NASEM (2019) identified three primary goals for food and agriculture to achieve by 2030: "(1) improving the efficiency of food and agricultural systems, (2) increasing the sustainability of agriculture, and (3) increasing the resiliency of agricultural systems to adapt to rapid changes and extreme conditions." For reasons already discussed, NASEM (2019) strongly recommends prioritizing multi-disciplinary, systems techniques to achieve the outlined goals.

As continued research enhances the understanding of beef production and additional production data is gathered, there is continuous need for updates and improvements to past models and their derivative equations (Hirooka, 2010). Once advancements in a specific field have been achieved, the key becomes determining their true impact and the optimal way to fit those advancements into the broader system. There are several more reasons to recreate or update beef production models. Growing computing power creates the possibility for more model complexity without sacrificing computing time. In addition, building models in more modern, open-source programming languages encourages application. Perhaps most importantly, model building provides the modelers with synthesized learning about how an entire system functions.

Over the years, lack of wide-spread understanding in modeling techniques and difficulty in model validation have likely limited the trust in many systems models to the model developers alone. Furthermore, as the multidisciplinary groups often required to build effective systems models disband or progress in career paths, their models tend to fall into disuse. Models without extensive documentation, updated programming language, or with extreme complexity often succumb to such a fate. Even as far back as Penning De Vries (1977) there were concerns regarding the tradeoffs between model complexity and usefulness: “Good scientific models are often too detailed or too speculative for those who want to apply them, whilst models used for predictive or management purposes are often too trivial or too crude to challenge scientific interest.”

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Objective

The present research objective was the development of a stochastic systems simulation model on an individual based, daily time step capable of accounting for the nutrition, reproduction, genetics, health, and economic conditions relevant to cow-calf production. The use of EFA to assess model validity in circumstances where real-world outcome data (e.g. weaning weight, reproductive rate, etc.) cannot be paired with respective input parameters (e.g. management, genetics, nutrition) was also investigated.

Materials and Methods

Model Design and Simulation for Validation

Simulated sire mature cow weight (MW) genetic potential (GP) ranged from 454 kg to 771 kg in 45 to 46 kg increments with sire peak lactation (PL) GP set to 6.8, 9, 11.3, or 13.6

kg/d. In total, 32 breeding systems (8 Sire MW GPs and 4 Sire PL GPs) with varying MW and PL genetics were simulated.

With the model parameterized for a goal of 100 breeding females exposed during the breeding season, each scenario herd is simulated 100 iterations. Each iteration runs for 24 production years (1995-2018) with historical inputs as specific as possible to the Flint Hills region for precipitation and temperature. A “production year”, as defined in the model, is the time from calving in year *i* to either calving in year *i*+1 or culling for each individual breeding female. Thus, the length of each production year will vary between individual animals. The five years 1995 through 1999 are used as burn-in years to allow for model stabilization following the exogenous parameter inputs in the initial year (1995) and are not reported in the results.

During the model verification process, five simulations of 20 iterations each were ran using the 590 kg MW – 11.3 kg/d PL scenario. For each simulation, the median kg weaned per cow exposed across all 20 iterations and production years 2000-2018 was determined. The coefficient of variation of the five median values was 0.5 percent. Given the small coefficient of variation and a greater than 12 hour run-time for a 100 iteration simulation, it was deemed that 100 iterations for each scenario was sufficient.

To determine the number of burn-in production years, within herd cow age distribution was assessed. The mean herd proportion for a given cow age across production years only changed at the third decimal place when progressively excluding production year 1995; production years 1995 and 1996; production years 1995, 1996, and 1997; production years 1995, 1996, 1997, and 1998; and production years 1995,1996,1997,1998, and 1999. Visual inspection also showed that cow herd age distribution at model initialization was well within the range of subsequent endogenous production year results. As a precautionary measure, production years 1995 through 1999 were considered burn-in years.

General Decision Rules

The model goal is to expose 100 females for breeding between May 1 and July 3 (63 days) each year. Heifer and cow breeding season start and end dates are identical. Pregnancy status is determined 60 days after the end of the breeding season. All non-pregnant females are sold at calf weaning. In addition, minimum culling levels are set for each age group (Appendix 2.1: Table 2.A1.12). If the percent non-pregnant within an age group has not reached the minimum level, voluntary culling (assumed to result from disposition, foot quality, udder quality, etc.) occurs until the minimum for each specific age group is reached. All 13-year-old cows at the time of pregnancy detection are culled at weaning. Heifer calves are kept to replace the culled females, plus an addition calculated from past cow losses (mortality, abortion, calf-loss before breeding season) that occur between weaning and the next breeding season. Replacement heifers are selected in order from oldest to youngest. If replacement heifer requirements exceed the number of raised heifers, Non-pregnant replacement heifers are purchased with traits matching the raised heifer population.

All calves are sold on the weaning date and weaned on the same date. The weaning date is set as the date upon which the oldest calf is 220 days old.

Bulls are not accounted for in the model. Because the goal of each scenario is to expose the same number of females for breeding, it assumed any cost differences from bulls would be minor.

Within the model, the grazing season spans from May 1 to October 31 (KSU and KDA, 2019). McMurry (2009) estimated average cow size at 612.25 kg (1350) pounds. The average full season cow-calf pair acreage allocation in the Flint Hills between 1995 and 2019 was 7.3 acres per pair (Dhuyvetter et al., 2009; KSU and KDA, 2017; KSU and KDA, 2019). Assuming a 1350 pound (612.25 kg) average cow weight between 1995 and 2019, the metabolic weight (weight^0.75) of a 612.25 kg (1350) pound cow was indexed as 1. For each scenario, 7.3 acres per pair allocation was changed according to the metabolic weight of the mean mature cow weight as a percentage of the metabolic weight of a 1350 pound cow (Appendix 2.1: Table 2.A1.5). The same acreage allocation adjustments were made for full season yearling heifer grazing and post-weaning grazing of replacement heifer calves from their base acreage allocations of 4 acres per head and 2.7 acres per head (Dhuyvetter et al., 2009; KSU and KDA, 2017; KSU and KDA, 2019), respectively (Appendix 2.1: Table 2.A1.5).

Genetics

In a recent BEEF magazine survey, 53% of respondents reported a predominantly Angus cow herd and 55% most recently purchased an Angus bull (Ishmael, 2020). The responses were not weighted for cow herd size. The simulated cow herd is assumed to have 100% Angus genetic makeup.

The MW GP for individual animals within the simulation is drawn from a normal distribution with the mean determined by averaging the sire and dam MW GPs for each simulated mating. Thus, each mating potentially generates a distribution with a unique mean. The standard deviation (sd) is set to 25.4 kg (56 pounds) for all MW GP distributions. The sd is based on a calculated 0.3 BIF accuracy from a parental average in which the parent expected progeny differences (EPDs) are known with 0.99 BIF accuracy (AAA, 2019a; BIF, 2010), which the model's omniscient nature enables. Within the model, MW GP is defined as mature cow weight at a body fat composition of 0.1889, body condition score (BCS) 5 on a 1 to 9 scale (NRC, 2016). Sire MW GP is static at the scenario defined level. Dam MW GP is her actual MW GP as determined in the stochastic method presently described.

The preliminary PL GP for each individual animal is determined in the same manner as MW GP, except that the sd for the GP normal distribution is arbitrarily set to 1 kg (2.205 pounds) as in reality, no genetic evaluations calculate an EPD for PL. Sire PL GP is static at the scenario defined level and Dam PL GP determination follows the same method as Dam MW GP.

Historical EPD trends by birth year for birth weight (BW) and weaning weight (WW) were gathered from the American Angus Association and then converted (multiply by two) to estimated breeding values (EBV) to account for genetic trends across the simulated time period (AAA, 2019b; Appendix 2: Table 2.A1.2). Although an increasing MW trend was also present (AAA, 2019b), it was assumed that the same BW and WW genetic trend occurred even with fixed sire MW GP. This can be interpreted as a breeding objective in which MW is held constant while maintain genetic improvement for BW and WW consistent with breed average. For any year *i*, Sire EBVs for BW and WW are the average EBVs for year *i*-2 through year *i*-5, assuming a sire is used four mating seasons and his first progeny are born when he is two-years-old. The sire EBV for WW and BW were then converted to a GP base representative of actual weaning weights, as follows, to simplify intra-model calculations.

Sire WW GP

$$Sire\ WW\ GP\ Base = 0.42 * 1400 + (Sire\ MW\ GP * 2.205 - 1400) * 0.125$$

where

Sire WW GP Base and *Sire MW GP* are in pounds.

Therefore:

$$Sire\ WW\ GP_i = Sire\ WW\ GP\ Base + Average\ Sire\ WW\ EBV_i$$

where

$Sire\ WW\ GP_i$ (pounds) = is the Sire WW genetic potential for calves born in year i

$$Average\ Sire\ WW\ EBV_i = (\Sigma_{i-2}^{i-5} AAA\ WW\ EBV_i)/4$$

where

$AAA\ WW\ EBV_i$ (pounds) = average WW EBV for Angus calves born in year i (AAA, 2019b).

Critical to the WW GP conversion is the assumption that a 100 kg deviation from 635 kg MW base causes a 12.5 kg directionally similar change in base WW GP (Doye and Lalman, 2011). Referencing actual calf weaning weight as percent of MW from Doye and Lalman (2011), Ramsay et al. (2017), and Scasta et al. (2015), 42 percent of 1400 pounds (635 kg) was used as a constant in the Sire WW GP Base equation. Applying the Sire WW GP Base and the Average Sire WW EBV for 1995 facilitates the assumption that calves born in 1995 and reported in Ramsay et al. (2017) had an adjusted 205 d weight equal to their genetic potential.

Sire BW GP Base was determined by regressing Adjusted BW on Adjusted WW (assuming 205 d adjusted WW was equal to genetic potential) using 2017 and 2018 born bull calf records from 424 Gelbvieh, Simmental, Red Angus, and respective Angus crosses (EPR, 2019) after converting bull WW to steer WW by a factor of 0.97 (Lee et al. 1997). The original constant of 60.202 was reduced to 54.202 to convert to an Angus base considering 2018 across breed BW EPD adjustment factors after converting to EBV units (Kuehn, 2018).

Sire BW GP

$$Sire\ BW\ GP\ Base = 0.037 * (Sire\ WW\ GP\ Base + Sire\ WW\ EBV_{1992}) + 54.202.$$

Therefore:

$$Sire\ BW\ GP_i\ =\ Sire\ BW\ GP\ Base\ +\ Average\ Sire\ BW\ EBV_i$$

where

Sire BW GP$_i$ (pounds) = is the Sire BW GP for calves born in year *i*

$$Average\ Sire\ BW\ EBV_i = (\Sigma_{i-2}^{i-5} AAA\ BW\ EBV_i)/4$$

where

AAA BW EBV$_i$ (pounds) = average BW EBV for Angus calves born in year *i* (AAA, 2019b).

Both WW and BW bases are on a male base. All GP mating calculations are based on steer WW GPs and bull BW GPs. Appropriate conversions to female phenotypes are described where relevant.

The preliminary BW and WW GPs for all breeding females in the initial year (1995) are calculated using the parental average GP distribution technique previously described, with the assumption that both parents have the average GPs for calves born in the years 1989-

1992. The sd for the BW GP distribution is 3.76 pounds (1.71 kg) and the sd for the WW GP distribution is 22 pounds (10 kg) with both GPs at a 0.3 BIF accuracy based on 0.99 parental EPD BIF Accuracy (AAA, 2019a; BIF, 2010). Preliminary BW and WW GPs for subsequent generations are calculated using the average sire GP for that year's calf crop, the dam's individual GP, and the stochastic process described previously.

Final PL, WW, and BW GPs are determined after accounting for intra-population genetic correlations between PL and MW (+0.14) (Morris and Wilton, 1976); WW and MW (+0.44) (AAA, 2019c); and between BW and WW (+0.29) (AAA, 2019c) by incorporating Cholesky decomposition techniques into the model (Hofert, 2013).

A BW heritability of 0.46 (AAA, 2019c) implies that 54% of the variance comes from environment. Thus, a progeny genetic BW EBV sd of 3.76 pounds from mating parents with 0.99 BIF accuracy suggests that BW variance from environment is 16.6 pounds. Therefore, individual phenotypic birthweight was modeled from a normal distribution with the individual's BW GP as the mean and 4.07 pounds as the sd. Phenotypic BW was further adjusted by dam age (BIF, 2010) and calf sex. Female birthweight phenotypes are 94% of their male equivalents (BIF, 2010; USDA, 2010). Original 205 d WW GP's are on a steer base with female WW GP's at 93% (Lee et al., 1997) of their steer equivalents. Adjustments to WW GP based on calf sex are made before calculating genetic pre-weaning average daily gain (ADG). Base pre-weaning ADG (BADG) potential for calf j is calculated with the following equation (BIF, 2010):

$$BADG_j = \frac{[(WW\ \mathrm{GP}_j - WW\ Dam\ Age\ Adjustment_j) - (BW\ \mathrm{GP}_j - BW\ Dam\ Age\ Adjustment_j)]}{205}$$

where:

WW GP_j = the 205 d WW GP for calf *j*, adjusted for calf sex,

WW Dam Age Adjustment$_j$ = BIF (2010) WW adjustment based on dam age and sex of calf *j*,

BW GP_j = the 205 d BW GP for calf *j*, adjusted for calf sex, and

BW Dam Age Adjustment$_j$ = BIF (2010) WW adjustment based on dam age and sex of calf *j*.

Thus, base potential for actual WW (BAWW) for calf *j* can be calculated as follows:

$$BAWW_j \; = \; Actual\ BW_j \; + \; BADG_{\ j} * Weaning\ Age_j$$

where

Weaning Age= calf *j* age in d at weaning.

$$Actual\ BW_j = \; rnorm(BW\ EBV_j, 4.07) - \; BW\ Dam\ Age\ Adjustment_j$$

where

rnorm(BW GP_j, 4.07*)* = a randomly drawn value for calf *j* from a normal distribution with mean equal to calf *j*'s BW GP and standard deviation equal to 4.07 pounds, as previously described.

Actual weaning weight is a function of calf weaning age and pre-weaning ADG subject to nutrient availability, and nutrient requirements according to NRC (2016) equations. Prior to d 80 postpartum, there is no limit on calf ADG. Calves grow according to NRC (2016) equations using whatever nutrients are available. At d 50, assuming a functional rumen, calves are allowed to eat forage, generally following Tedeschi and Fox (2009). At d 80, calf growth is capped to the calculated ADG need to reach their genetic potential. For calf age >= 80 d:

$$Max\ ADG_{jd}\ = \frac{BAWW_j -\ Calf\ Weight_{jd}}{Weaning\ Age_j - d}$$

where:

Max ADG_{jd} = the maximum ADG allowed for calf *j* on day *d* of age, and

Calf $\text{Weight}_{\text{jd}}$ = calf *j* body weight on day *d* of age

Such growth rules generate a similar pre-weaning growth as presented in Tedeschi and Fox (2009). Ultimately, calves are not allowed to outgrow their base potential for actual weaning weight.

Nutrition

Individual, daily nutrient requirements and intake of all cows and calves are calculated using NRC (2016) equations for net energy for maintenance (NEm) and net energy for gain (NEg). Weight, temperature, growth, gestation, and lactation are all accounted for depending on the individual's production phase. Monthly average temperature data for Manhattan, KS (HPRCC, 2019; Appendix 2.1: Table 2.A1.4) is included in the base maintenance NEm equation. Although not likely in real-world production, nutrition within the model is optimized by assuming individual management.

Daily net energy requirement for maintenance, gestation, and lactation (NEmR) for all animals, regardless of age is calculated as:

$$NEmR_{jd} = [0.0007 * (20 - Temp_{mi}) + 0.077] * CSBW_{jd}{}^{0.75} + NEmLG_{jd}$$

where

$NEmR_{jd}$ = NEmR (Mcal) for animal j on day d,

$Temp_{mi}$ = average temperature during month m and production year i,

$CSBW_{jd}$ = shrunk body weight of animal j on day d, and

$NEmLG_{jd}$ = net energy (Mcal) requirement for lactation and gestation for animal j on day d.

$$NEmLG_{jd} = NEmL_{jd} + NEmG_{jd}$$

where

$$NEmL_{jd} = 0.72 * Lact_d$$

where

$$Lact_d = \frac{n}{a * e^{k*n}} * AF.$$

$Lact_d$ = daily lactation in kg/d,

n = d postpartum rounded to the nearest integer week,

k = 0.1175, and

AF = 0.74 if cow year of age <=2, 0.88 if cow year of age = 3, or 1 if cow year of age = 1

$$a = \frac{1}{PL * k * e}.$$

$NEmG_{jd}$ is calculated as follows:

$$NEmG_{jd} = km * MEpreg_t$$

where

km = 0.576

$$MEpreg_t = \frac{NEpreg_t}{0.13}$$

where

$$NEpreg_t = \frac{[CBW_j * (0.05855 - 0.0000996 * t) * e^{0.03233 * t - 0.0000275 * t^2}]}{1000}.$$

CBW_j = actual birth weight of calf j, and

t = day of gestation

If a cow’s PL is less than 7 kg/d, NEmR is reduced by 12 percent (Montano-Bermudez et al., 1990). If a calf’s dam has a PL less than 7 kg/d, NEmR is reduced by 11 percent (Montano-Bermudez et al., 1990).

Daily dry matter intake (DMI) (kg/d) for cows >= two-years-old is calculated as (NRC 2016):

If t <= 93, then

$$DMI_d = CSBW^{0.75} * \frac{(0.0384 + 0.04997 * NEmD^2)}{NEmA} + 0.2 * Lact_d$$

else,

$$DMI_d = CSBW^{0.75} * \frac{(0.04631 + 0.04997 * NEmD_d{}^2)}{NEmA} + 0.2 * Lact_d.$$

$NEmD_d$ = ration nutrient density (NEm/kg DM) on day d, and

$NEmA$ = if $NEmD_d$ >= 1, then $NEmD_d$, else 0.95.

For weaned animals less than two-years-old DMI_d is determined by first calculating DMI as percent of body weight the following (NRC, 2016):

$$DMI_d = DMI\ PCT_d * CSBW_d$$

where

$$DMI\ PCT\ _d = \frac{1.2425 + 1.9218 * NEmD_d - 0.7259 * NEmD_d{}^2}{100}.$$

For each mean MW category a maximum limit to DMI PCT is assigned according to Appendix 2.1: Table 2.A1.8 Daily calf forage DMI is calculated from a slight modification to equation 25 in Tedeschi and Fox (2009). Equation 25 from Tedeschi and Fox (2009) tends to under-predict calf forage DMI, particularly at higher DMI levels, presumably at heavier calf weights and late in the lactation curve. In the present model, daily milk production (kg/d) replaced the static peak milk level variable in the original formulation. On average, Tedeschi and Fox (2009) equation 25 under-predicted calf forage DMI by 0.57 kg/d. Comparing the modified equation to the original equation at 6, 8, 10, and 12 kg/d PL over a 212 d nursing period with grazing nutrient density according to Appendix 2.1: Table 2.A1.6, the modified equation predicted daily forage DMI an average of 0.65 kg/d greater than the original equation. Considering the 0.57 kg/d under-prediction of Tedeschi and Fox (2009), the modified equation increased calf forage DMI to better align with the actual calf intake data in Fig. 5 of Tedeschi and Fox (2009).

Body weight gain (kg/d) and BCS (1-9) are calculated daily for each animal. Individual daily shrunk body gain (SBG_{jd}) for animals <= three-years-old is calculated as follows (NRC, 2016):

$$SBG_{jd} = \frac{12.341 * {EBW_{jd}}^{-0.6837} * {NEgI_{jd}}^{0.9116} + EBL_{jd}}{0.956}$$

where:

$$EBW_{jd} \ = \ 0.891 * EQSBW_{jd}$$

where:

$$EQSBW_{jd} \ = \frac{478}{MW_j} * CSBW_{jd}$$

$$NEgI_{jd} = \max(NEgD_d * \ (DMI_{jd} - NEmR\ DMI_{jd}), 0)$$

where:

$NEgD_d$ = net energy for gain (NEg) ration density (Mcal/kg DM) on day *d*

$NEmR\ DMI_{jd}$ = DMI required to meet NEmR

Empty body weight loss (EBL) for animal *j* on day *d* is calculated by (NRC, 2016):

If $NEmI_{jd} < NEmR_{jd}$, then

$$EBL_{jd} = \frac{NEmI_{jd} - NEmR_{jd}}{Mcal\ kg\ BCS\ Loss}$$

else

$$EBL_{jd} = 0$$

where:

$NEmI_{jd}$ = NEm intake (Mcal) for animal *j* on day *d*

Mcal kg BCS Loss = Mcal required to lose 1 kg EBW at a given BCS according to Appendix 2.1: Table 2.A1.9.

For animals <= two-years-old daily BCS is determined by calculating total body fat (BF) (kg) as a percentage of SBW and then rounding to the nearest BCS according to Appendix 2.1: Table. 2.A1.11. Daily BF gain (BFG) is calculated by (NRC, 2016):

If $NEmI_{jd} > NEmR_{jd}$, then

$$BFG_d = \max(0.15 * NEgI_d - 0.0057 * {NEgI_d}^2 - 0.162, 0)$$

else

$$BFG_d = EBL_d$$

For cows four-years-old or greater, individual, daily shrunk body weight change is determined by the following:

$$SBG_{jd} = \frac{EBG_{jd} + EBL_{jd}}{0.956}$$

where if $NEmI_{jd} < NEmR_{jd}$, then

$$EBL_{jd} = \frac{NEmI_{jd} - NEmR_{jd}}{Mcal\ kg\ BCS\ Loss}$$

and

$$EBG_{jd} = 0$$

else

$$EBL_{jd} = 0$$

$$EBG_{jd} = \frac{NEmI_{jd} - NEmR_{jd}}{Mcal\ kg\ BCS\ Gain}$$

where:

Mcal kg BCS Gain = Mcal required to gain 1 kg EBW at a given BCS according to Appendix 2.1: Table 2.A1.9.

For individual animals four-years-old or greater, daily BCS is determined by calculating CSBW as a percentage of mature shrunk body weight (MSBW) (BCS 5) and rounding to the nearest BCS classification according to Appendix 2.1: Table 2.A1.9. For three-year-old cows, BCS is calculated in both the manner for animals two-years and younger and the manner for 4-years and older. The final daily BCS for three-year-olds is the maximum of the two methods. Decision rules are designed to maintain all post-weaning animals at BCS 5 or 6, although it is possible to fall outside that window under certain nutrient availability and intake conditions.

The Flint Hills bluestem based grazing season is parameterized to occur between May 1 and October 31 annually with forage nutrient density peaking in April-June at 1.48 megacalories (Mcal) NEm per kg dry matter (DM) and 0.9 Mcal NEg per kg DM (Kuhl et al., 1993; Appendix 2.1: Table 2.A1.6). In July and August, forage Mcal NEm and NEg per kg DM are 1.1 and 0.54, respectively. September through March Mcal NEm and NEg per kg dry matter are 0.71 and 0.18, respectively (Kuhl et al., 1993; Appendix 2.1: Table 2.A1.6). Total forage production per acre is estimated using a linear regression equation with cumulative precipitation for Manhattan, KS (HPRCC, 2019; Appendix 2.1: Table 2.A1.4) between January and August and the percent of forage remaining at the end of the prior grazing season as input factors. The regression equation was estimated using Flint Hills grazing data from 1958-1965 (Launchbaugh and Owensby, 1978) paired with cumulative precipitation for Manhattan, KS for the corresponding years (HPRCC, 2019). Based on accumulated forage intake, forage production per acre, stocking rate, and a 25% forage waste parameter (Ogle and Brazee, 2009) animals are removed from grazing prior to November 1, if the percent of forage remaining falls below 40%. While grazing, if an animal, excluding nursing calves, is below BCS 5 with a negative energy balance she receives the 60% alfalfa, 40% corn supplement ration (1.63 Mcal NEm per kg dry DM, 1.02 Mcal NEg per kg DM) until her NEm and NEg requirements are met or at most 20% daily DMI.

Outside the grazing season, cows are fed a 73% alfalfa, 19% wheat straw, and 8% corn base ration with 1.2 Mcal NEm per kg DM and 0.64 Mcal NEg per kg DM. With the exception of nursing calves, if an animal has a BCS greater than 6, daily DMI is restricted to 70% of what is required to meet NEm requirements until the individual is BCS 6 or below. If a cow is below BCS 5 with a negative energy balance the supplement ration is added to her ration mix until NEm and NEg requirements are met, subject to a cost minimizing linear programming model (MLPM) with DMI constraints. If there is no solution to the MLPM, the supplement ration replaces 40% of the base ration. The linear programming model is constructed as follows:

Minimize Objective Function:

$$Ration\ Expense_{jd} = x_{jd} * BRP_d + y_{jd} * SRP_d$$

subject to constraints:

$$x_{jd} * NEgBR + y_{jd} * NEgSR \geq NEgR_{jd} + NEgBR * \frac{NEmR_{jd}}{NEmBR} \tag{1}$$

$$x_{jd} * NEgBR + y_{jd} * NEgSR \geq NEgR_{jd} + NEgSR * \frac{NEmR_{jd}}{NEmSR} \tag{2}$$

$$x_{jd} * NEmBR + y_{jd} * NEmSR \geq NEmR_{jd} \tag{3}$$

$$x_{jd} * \frac{1}{DMI\ PCT_{jd}} + y_{jd} * \frac{1}{DMI\ PCT_{jd}} \geq CSBW_{jd} \tag{4}$$

$$x_{jd} + y_{jd} \leq DMI_{jd} \tag{5}$$

$$x_{jd} \leq Available\ BR_{jd} \tag{6}$$

$$x_{jd} \geq 0 \tag{7}$$

$$y_{d} \geq 0 \qquad (8).$$

Constraints 1 and 2 ensure that NEg in the final ration mix for animal *j* on day *d* meets or exceeds the NEg requirement for animal *j* on day *d*. Constraint 3 ensures that NEm in the final ration mix for animal *j* on day *d* meets or exceeds the NEm requirement for animal *j* on day *d*. DMI as a percent of shrunk body weight is controlled by constraint 4. Constraint 5 ensures that DMI (kg) does not exceed that previously calculated according to NRC (2016) equations and model rules as previously described. Constraint 6 holds base ration intake equal to or less than the maximum available allocation for animal j on day d. Non-negativity is controlled by constraints 7 and 8. See Table 2.1 and Table 2.2 for MLPM variable description.

Table 2.1. MLPM decision variable descriptions.

Variable	**Description**
x_{jd}	animal *j* base ration intake on day *d* (kg DM)
y_{jd}	animal *j* supplement ration intake on day *d* (kg DM)

Table 2.2. MLPM parameter variable descriptions.

Variable	**Description**
$Ration\ Expense_{jd}$	animal *j* ration expense (USD) on day *d*
BRP_d	base ration price on day *d* (USD/kg)
SRP_d	supplement ration price on day *d* (USD/kg)
NEgBR	base ration NEg density (Mcal/kg DM)
NEgSR	supplement ration NEg density (Mcal/kg DM)
$NEgR_{jd}$	animal *j* required NEg on day *d* (Mcal)
$NEmR_{jd}$	animal *j* required NEm on day *d* (Mcal)
$DMI\ PCT_{jd}$	animal *j* DMI as percent of $\mathrm{CSBW}_{\mathrm{jd}}$ on day *d*
$CSBW_{jd}$	animal *j* CSBW on day *d* (kg)
$Available\ BR_{jd}$	maximum base ration available (kg) on day *d* for animal *j* based on animal type according to Appendix 2.1: Table 2.A1.10

Calf nutrition calculations and rules are similar to those of mature animals, with the addition of milk in the diet per the dam's daily production. Mcal NEm and NEg per kg liquid milk is set to 0.55 and 0.33, respectively (Parkins et al. 1977). Calves consume only milk through 50 d postpartum. Calves are not offered creep feed, but will be fed the cow supplement ration as needed if pulled off grass before weaning. Daily calf DMI is calculated from Tedeschi and Fox (2009), as previously described. Pertinent to the Tedeschi and Fox (2009) equation, forage Mcal digestible energy (DE) per kg is 2.86 for April-June, 2.12 for July and August, and 1.89 for September through March. Fed ration DE is 3.08 Mcal/kg for all months (Appendix 2.1: Table 2.A1.6).

Reproduction

Age at first estrus for each individual replacement heifer is the maximum of a randomly drawn value from a normal distribution with mean=300 and standard deviation=20 (Diskin and Kenny, 2014) or the day a heifer reaches 40% of her mature weight (Davis and Wettemann, 2009).

Each cow’s postpartum interval (PPI) (d between calving and first postpartum estrus) is drawn from a pert distribution according to parity, BCS, and dystocia (Appendix 2.1: Table 2.A1.11) (Graham, 1982; Doornbos et al., 1984; Rutter and Randel, 1984; Bellows et al., 1988; Houghton et al., 1990; Ciccioli et al., 2003; Berardinelli et al., 2005; Cushman et al., 2007; Endecott et al., 2007; Lents et al., 2008). If a cow experiences dystocia, the subsequent increase in her PPI is drawn from a truncated random normal distribution with mean= 10 d, standard deviation= 3 d, and lower bound = 0 d (Doornbos et al., 1984; Bellows et al., 1988).

The mean herd wide dystocia risk for all multiparous cows and primiparous cows with calf BW<90 pounds (40.82 kg) is 0.05 (sd= 0.01, lower bound= 0) (McDermott et al. 1990, USDA, 2008). The mean herd wide dystocia risk for primiparous cows with calf BW >= 90 pounds is 0.08 (sd= 0.01, lower bound= 0).

Following first estrus for a given production year, each individual's estrous cycle is simulated with d between estrus drawn from a truncated normal distribution with mean= 21, sd= 0.75, upper bound= 24, and lower bound= 18. If a female is not pregnant and an estrus day occurs during the breeding season she has an opportunity to become pregnant (Appendix 2.1: Table 2.A1.11). After becoming pregnant there is daily abortion risk (Appendix 2.1: Table 2.A1.11). If a female aborts before the end of the breeding season, she has the opportunity to establish one more pregnancy. Preliminary gestation length for each pregnant female is randomly drawn from a normal distribution (mean= 285 d, sd= 5), before being adjusted through Cholesky decomposition methods to match the +0.30 genetic correlation between calf BW and gestation length (Gregory et al., 1995; Hofert, 2013).

Health

Calf morbidity and calf mortality prior to weaning are binary outcomes determined daily. Within the model, a calf may experience morbidity once, at most. The daily morbidity probability for each calf within a simulation iteration is drawn from truncated random normal distributions based on calf age and dystocia occurrence (Appendix 2.1: Table 2.A1.13). The daily probability of mortality is drawn from a truncated random normal distribution. Eight different distributions represent potential combinations of age, dystocia occurrence, and mortality occurrence (Appendix 2.1: Table 2.A1.13). For both morbidity and mortality, calf age is separated into neonatal (<=3 d old) and post-neonatal to weaning (>3 d old to weaning).The same daily probability for morbidity and mortality applies to each calf within the same category (age, dystocia occurrence, prior morbidity) for all years within a single simulation iteration.

Mortality is a daily, binary outcome for both post-weaning replacement heifers (before establishing first pregnancy) and females in the breeding herd. The two age categories have different truncated random normal distributions from which daily mortality risk is drawn at the start of each simulation iteration (Appendix 2.1: Table 2.A1.13). For a given iteration, the same daily mortality risk applies to each female.

Validation Procedures

Three different validation procedures were applied to simulation output for production years 2000 through 2018:

1) Expert panel review,

2) Descriptive statistics comparing model output to historical cow-calf production data, and

3) Exploratory factor analysis on a combined data set of model output and actual historical cow-calf production data.

Expert Panel Review

The model was simulated 100 iterations per breeding system scenario according to the previously described parameters and design. Graphical output for 17 different simulation outcome variables by MW and PL combination were presented to a six person panel with combined expertise spanning veterinary medicine, animal breeding and genetics, ruminant nutrition, agricultural economics, and beef production modeling. Table 2.3 provides further expert panel details. Variable distributions were aggregated across production years 2000 through 2018 and median values were displayed by cow type and production year. Variables presented ranged from growth and reproductive traits to nutrition and herd demographics. Each output variable was reviewed and discussed in absolute value terms and relative to other scenarios.

Table 2.3. Expert panel qualifications and experience.

Expert Panel Reviewer	Qualifications	Years of Professional Experience
1	DVM, PhD (Animal Sciences and Industry)	>30
2	PhD (Animal Breeding)	>25
3	PhD (Agricultural Economics)	>15
4	DVM, MS	>20
5	DVM, PhD (Epidemiology)	>15
6	PhD (Ruminant Nutrition)	>10

Descriptive Statistics: Model Output vs Real-World Production Data

Individual Data

Individual calf data from North Dakota State University's CHAPS program (CHAPS, 2020) from the years 2000 through 2017 was paired with individual cow data from the same data set by matching herd, year, and cow identification number. Variables considered were actual calf birth weight (ABW), calf weaning age (WAGE), calf 205 d adjusted weaning weight (ADJ WW), cow age (CAGE), and cow weight at weaning (MWW). All weight variables were converted to kg at 2.205 pounds equals 1 kg. MWW was classified by rounding to the nearest simulated scenario MW class (e.g. 560 kg MWW rounds to 544 kg MW class). After classifying to MW, MWW was no longer considered. The model assumes cows reach maturity at four-years-old. Thus, all CHAPS records with CAGE less than 4 were removed to prevent confounding MWW with maturity. Although BCS at weaning is a potential variable, few cows in the paired data set had a BCS record. Therefore, BCS was not considered. The model simulation was parameterized to describe average Angus BW and WW genetics; however, implementing an Angus breed requirement to the paired data in addition to the other described data requirements yielded only 235 records. After all qualifications, the data set consisted of 5,025 unique records of ABW, WAGE, ADJ WW, CAGE, and MW from 1,642 individual cows and 6 herds. Table 2.4 reports the percent of total records in each MW category for the final data set (IND CHAPS).

Table 2.4. Percent of total records in each MW category for IND CHAPS data set consisting of 5025 unique records from 1642 cows and 6 herds.

MW Category (kg)	Percent of Total Records (%)
454	0.7
499	2.9
544	8.3
590	17.5
635	19.3
680	20.5
726	15.9
771	14.8

With variables matching IND CHAPS, 5025 total records were randomly sampled (IND MOD) from a combined dataset of all cow types and production years 2000 to 2017. No requirements were applied for percent of sample in MW category (Table 2.5) or number of unique cows.

Table 2.5. Percent of total records in each MW category for the model sample data set consisting of 5025 unique records.

MW Category (kg)	Percent of Total Records (%)
454	12.7
499	12.0
544	12.6
590	12.6
635	13.2
680	12.2
726	11.9
771	12.8

Box-plots identifying the median, 25th percentile, and 75th percentile for each variable by data source (IND CHAPS or IND MOD) and MW category were generated and evaluated.

Herd Data

Yearly herd level data was also provided by the CHAPS program (CHAPS, 2020). Using herd data from 2000 to 2017, selected yearly records were required to expose 75 or more females for breeding and have complete records for mean actual calf birthweight (MBRTWT), for mean calf weaning age (MAGE), mean pre-weaning ADG (MADG), mean cow age (MCAGE), percent pregnant per cow exposed (PREGPERC), percent pregnancy loss per cow exposed (PREGLP), and percent calf mortality per calf born

(CALFL2). 422 unique yearly records from 39 herds met the specifications (HERD CHAPS). Data scarcity for mean cow weight and mean cow BCS prohibited their inclusion.

To generate a comparable sample from model simulated output, yearly herd level data for production years 2000 through 2017 was selected from one iteration each of the 32 simulated breeding system scenarios. All 18 years from each of the 32 scenarios were pooled together, then 422 yearly records were randomly selected (HERD MOD). Box-plots identifying the median, 25th percentile, and 75th percentile for each variable by MW-PL combination were generated. HERD CHAPS records remained aggregated as cow type was not identified.

Exploratory Factor Analysis: Model Output vs Real-World Production Data

Individual data

IND CHAPS and IND MOD were combined to form a data set 10,050 records. The psych package (Revelle, 2019) was applied in R statistical software (R Core Team, 2019) to perform EFA. Principal axes factoring (PAF) was used to extract two latent factors from the combined individual data. PAF does not rely on multivariate normality assumptions (Osborne, 2014). The maximum PAF iterations parameter was set to 100 and was not reached. The number of factors to extract was determined through parallel analysis (Osborne, 2014). Factor loadings were rotated by “oblimin” rotation (Osborne, 2014; Revelle, 2019). Factor scores were estimated using the Thurstone method (Grice, 2001; Thurstone, 1935).

Herd Data

HERD CHAPS and HERD MOD were combined to form a data set with 844 records. PAF was applied to extract three latent factors. All other EFA methods match those already described.

Results and Discussion

Expert Panel Review

Further explanation was provided on specific topics of interest not originally presented to the panel. The expert panel had no objections to model output, agreeing that the both the absolute and comparative output seemed reasonable given their experiences and expectations.

Descriptive Statistics: Model Output vs Real-World Production Data

Individual Data

The interquartile box-plots displayed in Fig. 2.1 and Fig. 2.2 show that compared to the six CHAPS herds contributing to IND CHAPS, model for ABW and ADJ WW was lower across all MW categories. Such a difference could be attributed to a number of factors including differences in growth genetics and nutrient availability. One quarter of the modeled scenarios include PL genetics at the low 6.8 kg/d level. The presence or absence of creep feed was not identified in CHAPS data. Although it may exist, an adequate daily growth model based on NEm and NEg intake for nursing calves was not found in the literature. Thus, growth equations for heavier calves from NRC (2016) were extrapolated to lighter weights. Furthermore, most growth equations are based on decades-old research that may not describe the current beef cattle population as well as the population upon which they were derived.

Nonetheless, model output for ABW and ADJ WW still fall in the range of values found in the industry. Simultaneously, greater values for ABW and ADJ WW by MW in IND CHAPS compared to the same measures in IND MOD is consistent with the 0.29 genetic correlation between birth weight and weaning weight in the modern Angus population (AAA, 2019c). The rate of change in ABW and ADJ WW across different MW categories also appears similar between data sources suggesting that model comparisons between cow types could be informative.

Median WAGE and CAGE (Fig. 2.3 and Fig. 2.4) appeared relatively similar between data sources, although WAGE showed a wider interquartile range across all MW categories in IND CHAPS compared to IND MOD. This finding is reasonable considering the only difference in modeled scenarios is MW-PL combination, while herd to herd and year to year management decisions likely vary within CHAPS data.

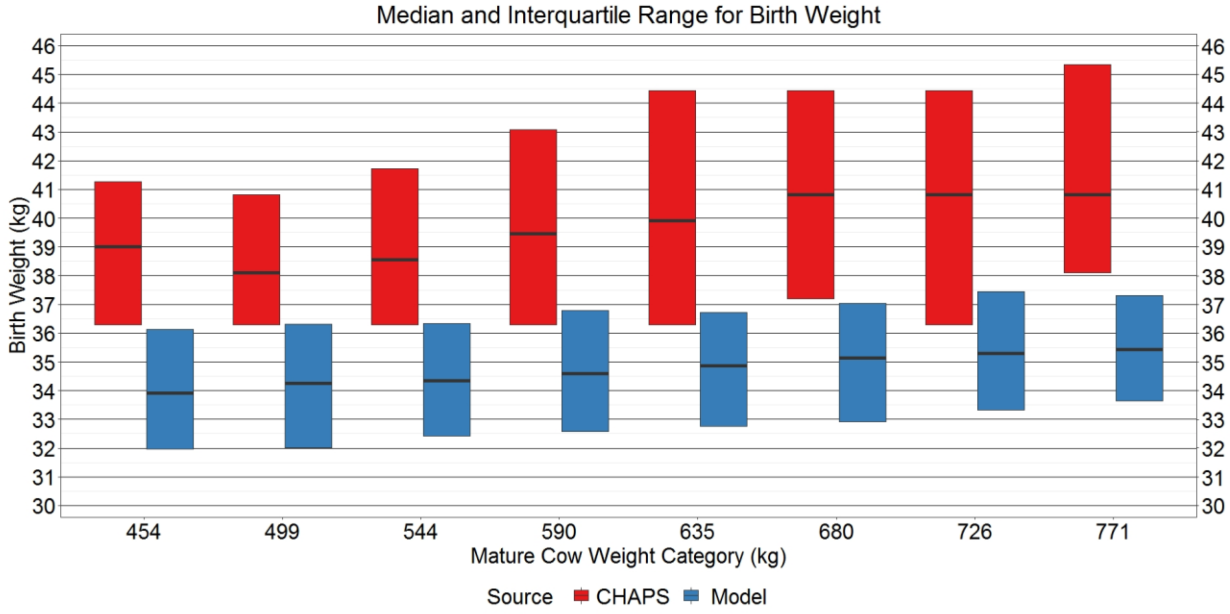

Figure 2.1. Boxplots representing the median, 25th percentile, and 75th percentile for individual calf birth weight from IND CHAPS and IND MOD.

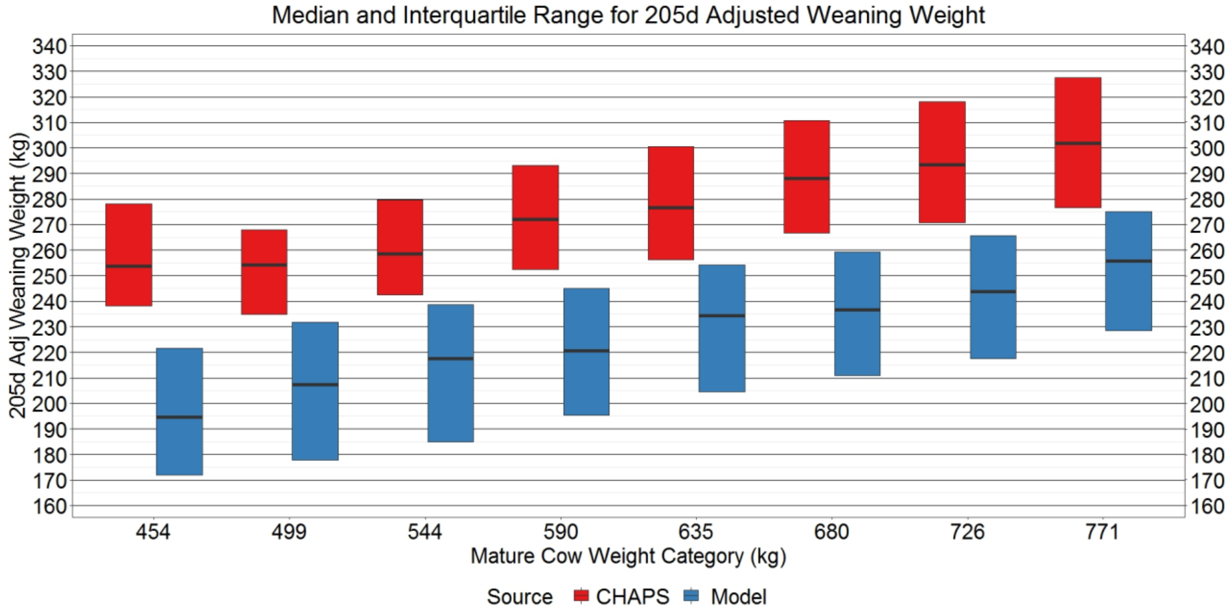

Figure 2.2. Boxplots representing the median, 25th percentile, and 75th percentile for individual calf 205d adjusted weaning weight from IND CHAPS and IND MOD.

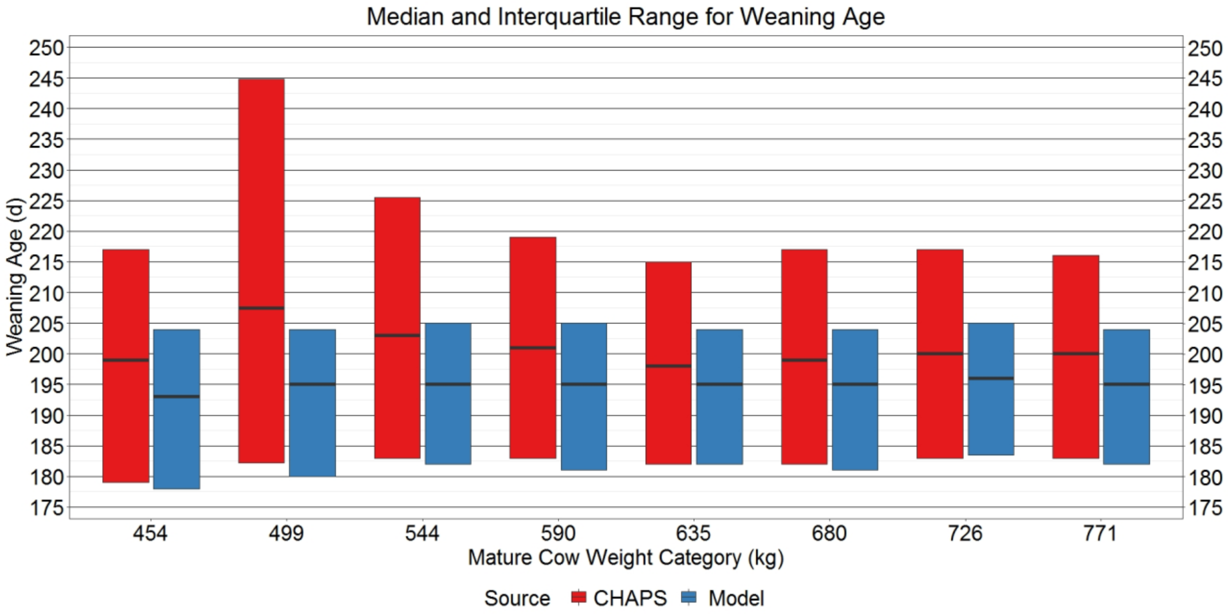

Figure 2.3. Boxplots representing the median, 25th percentile, and 75th percentile for individual calf weaning age from IND CHAPS and IND MOD.

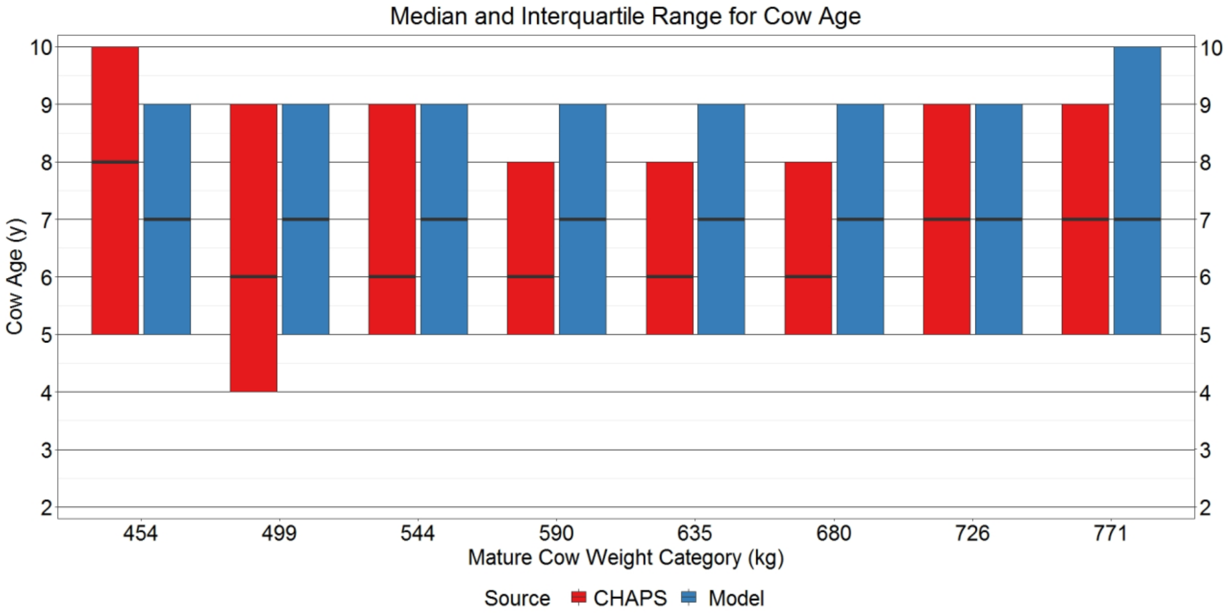

Figure 2.4. Boxplots representing the median, 25th percentile, and 75th percentile for individual cow age from IND CHAPS and IND MOD.

Herd Data

Yearly birth weight, growth, and age variables by herd (Fig. 2.5 through Fig. 2.8) suggest similar conclusions to those discussed at the individual animal level. Wider interquartile ranges in Fig. 2.5 through Fig. 2.7 for HERD CHAPS are also reasonable considering the data are not identified by cow type and the likely management variation across the 39 herds contributing to HERD CHAPS. Reproduction and survivability traits appear comparable between data sources (Fig. 2.9 through Fig. 2.11) with a slight advantage to the CHAPS herds. With the model designed and parameterized to describe industry averages, it is not surprising that herds submitting CHAPS data display an advantage in several traits, if stringent record keeping is associated with progressive, diligent management.

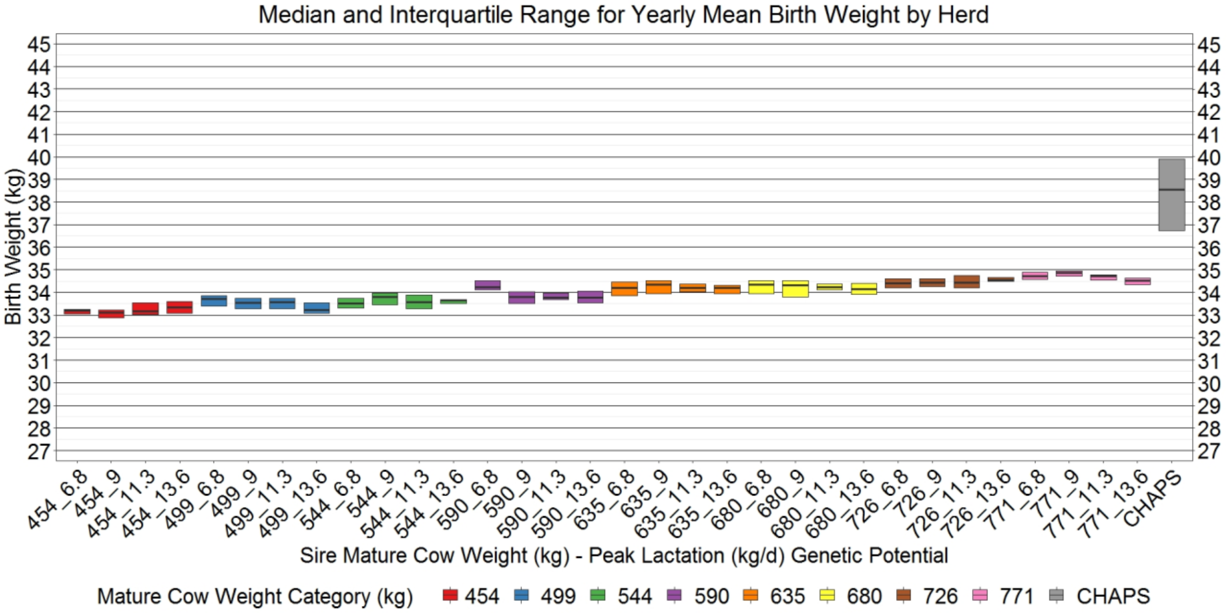

Figure 2.5. Boxplots representing the median, 25th percentile, and 75th percentile for yearly mean calf birth weight by cow MW and PL category combination from Herd MOD and HERD CHAPS. MW and PL category could not be identified for HERD CHAPS

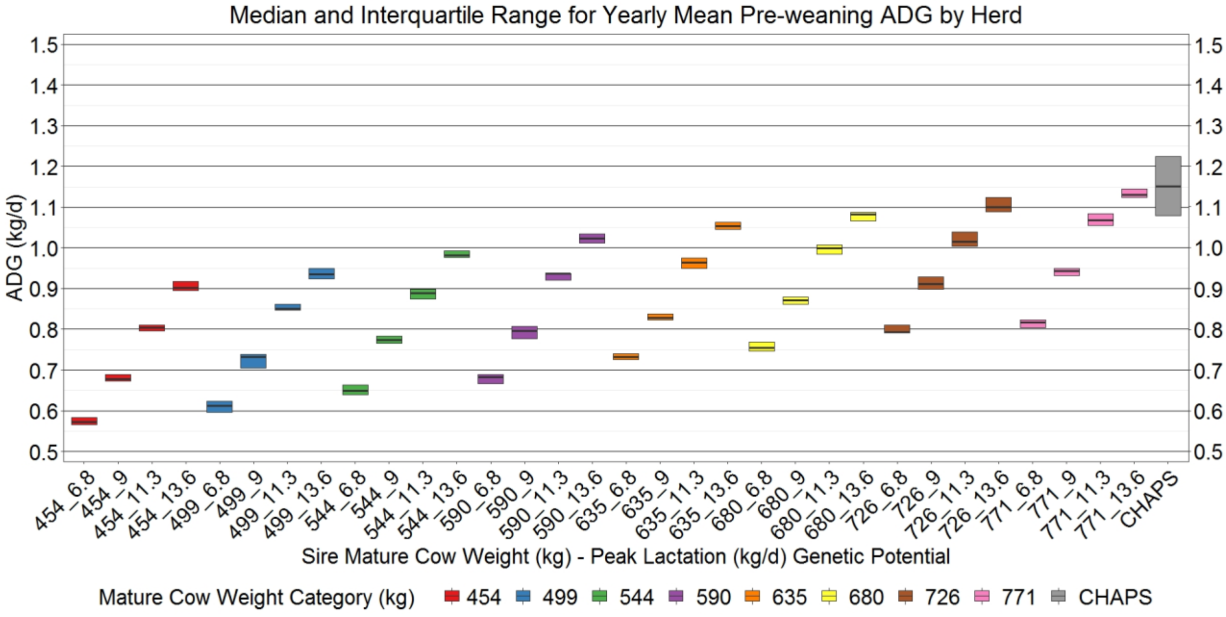

Figure 2.6. Boxplots representing the median, 25th percentile, and 75th percentile for yearly mean pre-weaning ADG by cow MW and PL category combination from Herd MOD and HERD CHAPS. MW and PL category could not be identified for HERD CHAPS.

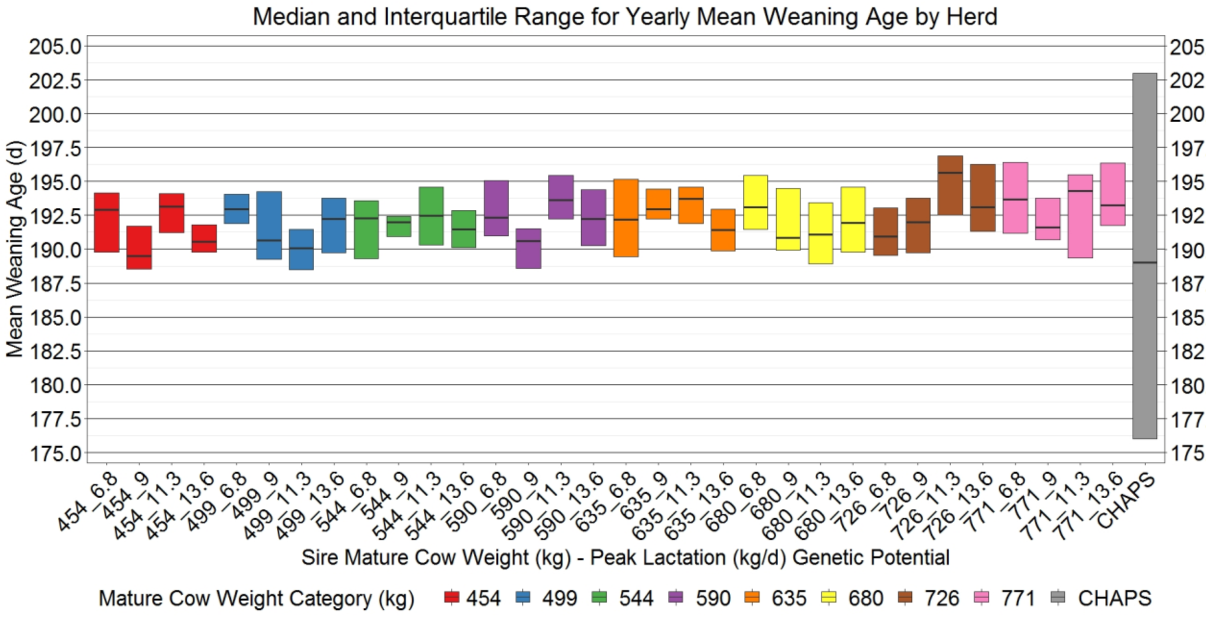

Figure 2.7. Boxplots representing the median, 25th percentile, and 75th percentile for yearly mean weaning age by cow MW and PL category combination from Herd MOD and HERD CHAPS. MW and PL category could not be identified for HERD CHAPS.

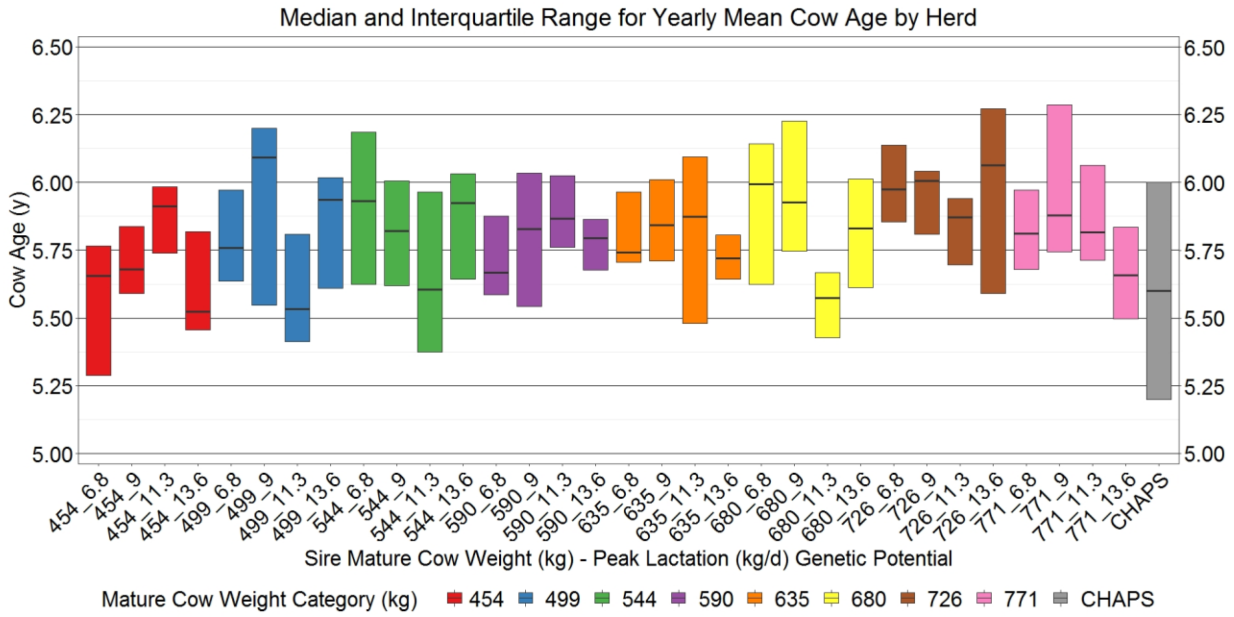

Figure 2.8. Boxplots representing the median, 25th percentile, and 75th percentile for yearly mean cow age by cow MW and PL category combination from Herd MOD and HERD CHAPS. MW and PL category could not be identified for HERD CHAPS.

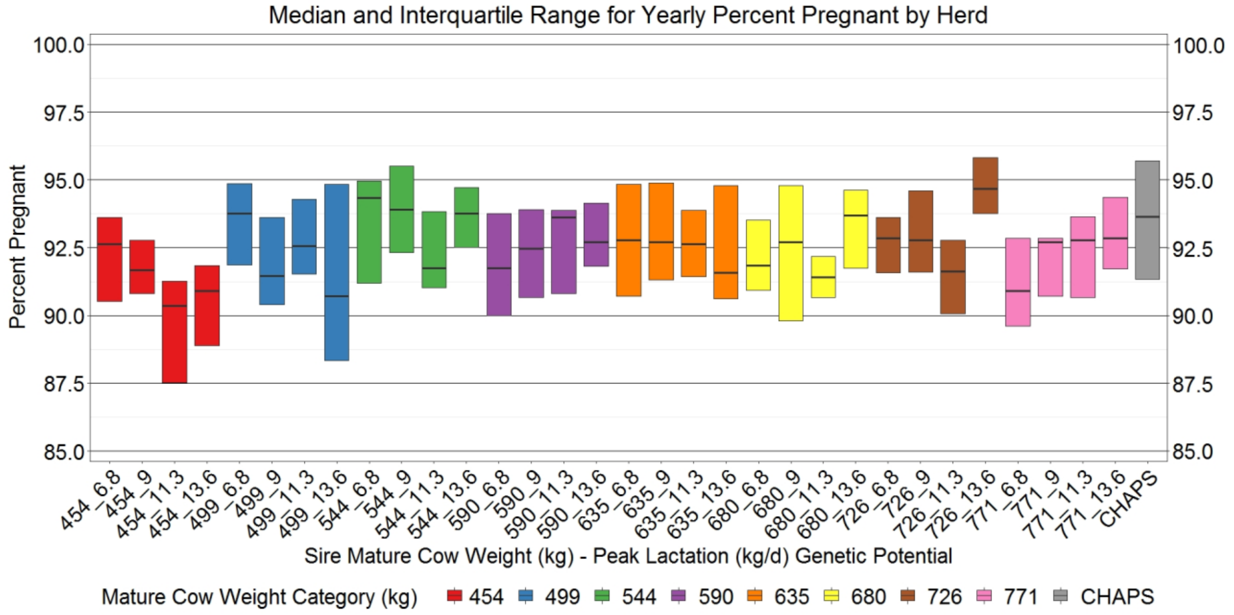

Figure 2.9. Boxplots representing the median, 25th percentile, and 75th percentile for percent pregnant per cow exposed by cow MW and PL category combination from Herd MOD and HERD CHAPS. MW and PL category could not be identified for HERD CHAPS.

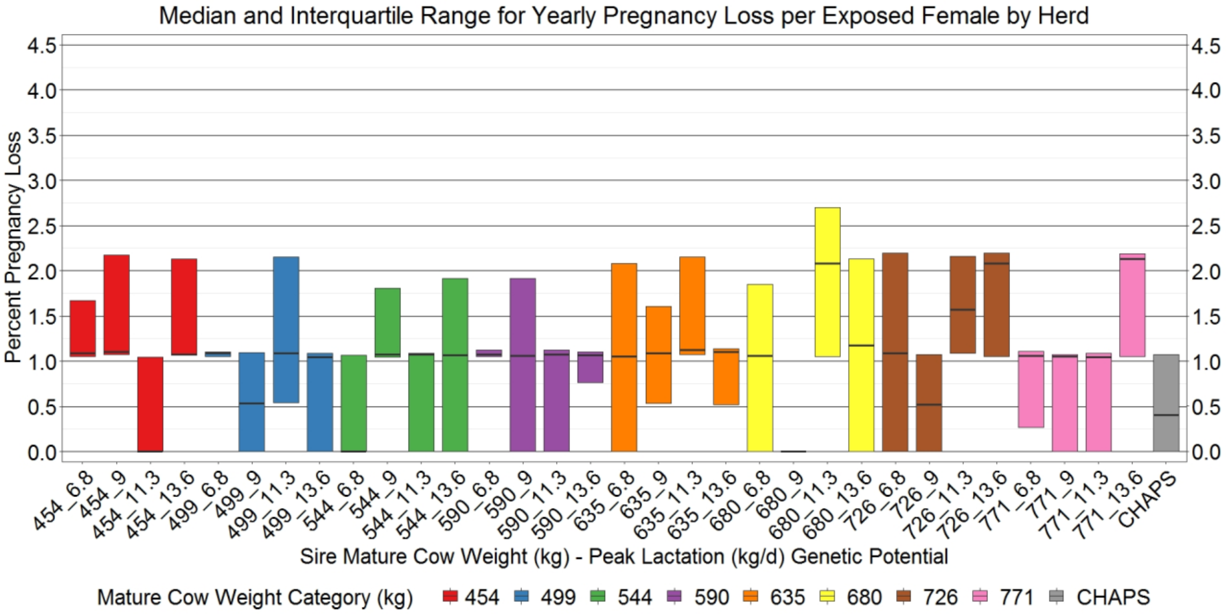

Figure 2.10. Boxplots representing the median, 25th percentile, and 75th percentile for percent pregnancy loss per cow exposed by cow MW and PL category combination from Herd MOD and HERD CHAPS. MW and PL category could not be identified for HERD CHAPS.

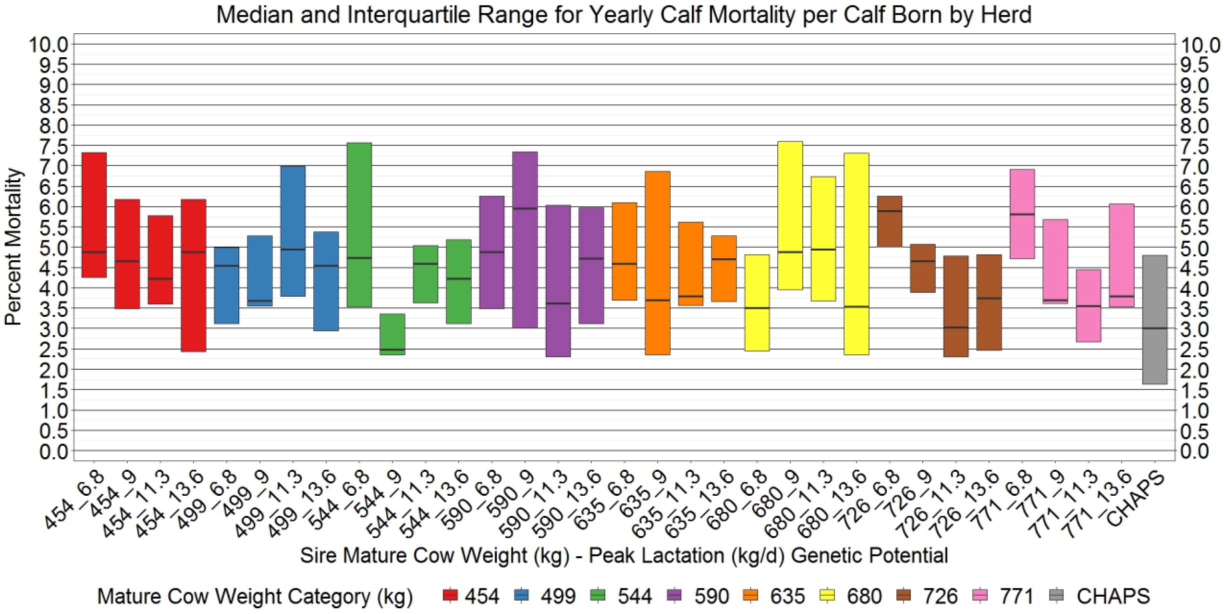

Figure 2.11. Boxplots representing the median, 25th percentile, and 75th percentile for percent calf mortality per calf born by cow MW and PL category combination from Herd MOD and HERD CHAPS. MW and PL category could not be identified for HERD CHAPS.

Exploratory Factor Analysis: Model Output vs Real-World Production Data

Individual data

Thirty-two percent of total variance in the combined individual data set can be attributed to two latent factors. The variable factor loadings plotted in Fig. 2.12 (blue lines) suggest a primary underlying factor influencing ABW and ADJ WW. Another factor appears to influence weaning age. Factor scores for all 10,050 records are plotted in Fig. 2.12. Multivariate normal data ellipses spanning two sd are drawn around each data source. Similar to analysis through descriptive statistics, EFA suggests increased ABW and ADJ WW for calves from the CHAPS data with IND MOD data from heavier MW categories aligning more closely with IND CHAPS. Similar age traits match the descriptive statistics as well. The consistent generalities between descriptive statistics and EFA is reassuring.

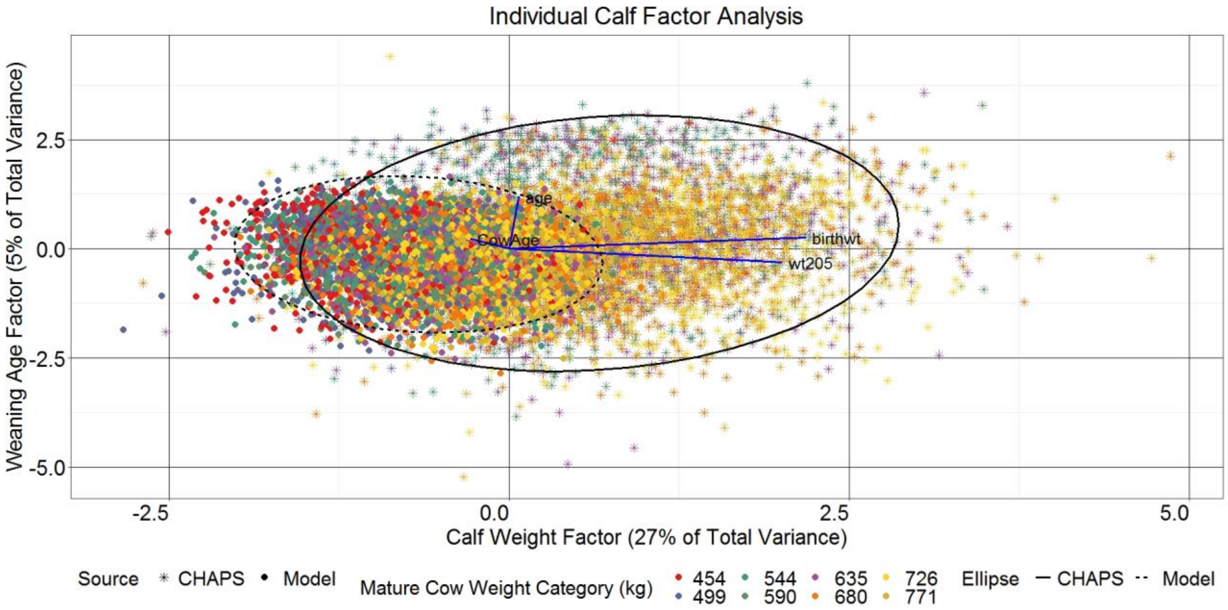

Figure 2.12. Individual calf factor score plot. birthwt = actual calf birth weight (ABW), wt205 = calf 205 d adjusted weaning weight (ADJ WW), age = calf weaning age (WAGE), CowAge = cow age (CAGE), and Mature Cow Weight = MW category (MW). Blue lines represent variables' direction and magnitude of influence based on their factor loadings. Data ellipses represent the two sd factor score coordinate boundary.

Herd Data

A three factor model described 3 percent of the total variance in the combined herd level data (Fig. 2.13 through Fig. 2.15). A common factor that seemingly influences calf weight accounted for 20 percent of total variance. Factors that appear to describe reproductive and age traits accounted for ten percent and six percent of total variance, respectively. Encouragingly, Fig. 2.13 through Fig. 2.15 support all the same conclusions previously discussed.

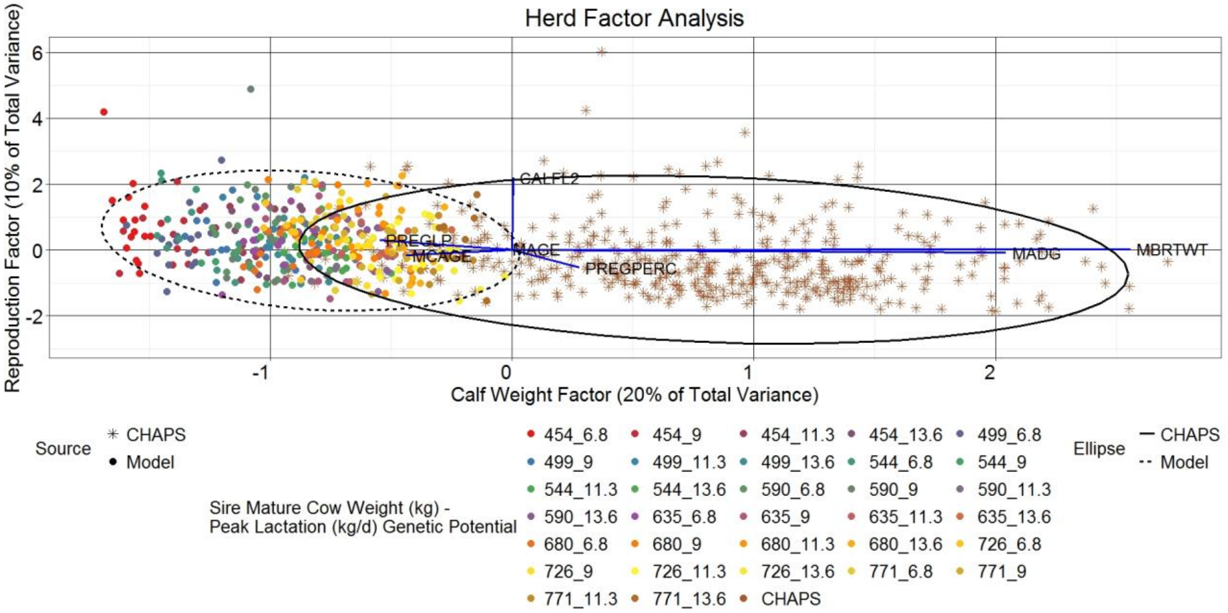

Figure 2.13. Yearly herd data factor score plot Reproduction Factor by Calf Weight Factor. MBRTWT = mean actual calf birthweight, MAGE = mean calf weaning age, MADG = mean pre-weaning ADG, MCAGE = mean cow age, PREGPERC = percent pregnant per cow exposed, PREGLP = percent pregnancy loss per cow exposed, and CALFL2 = percent calf mortality per calf born. Blue lines represent variables' direction and magnitude of influence based on their factor loadings. Data ellipses represent the two sd factor score coordinate boundary.

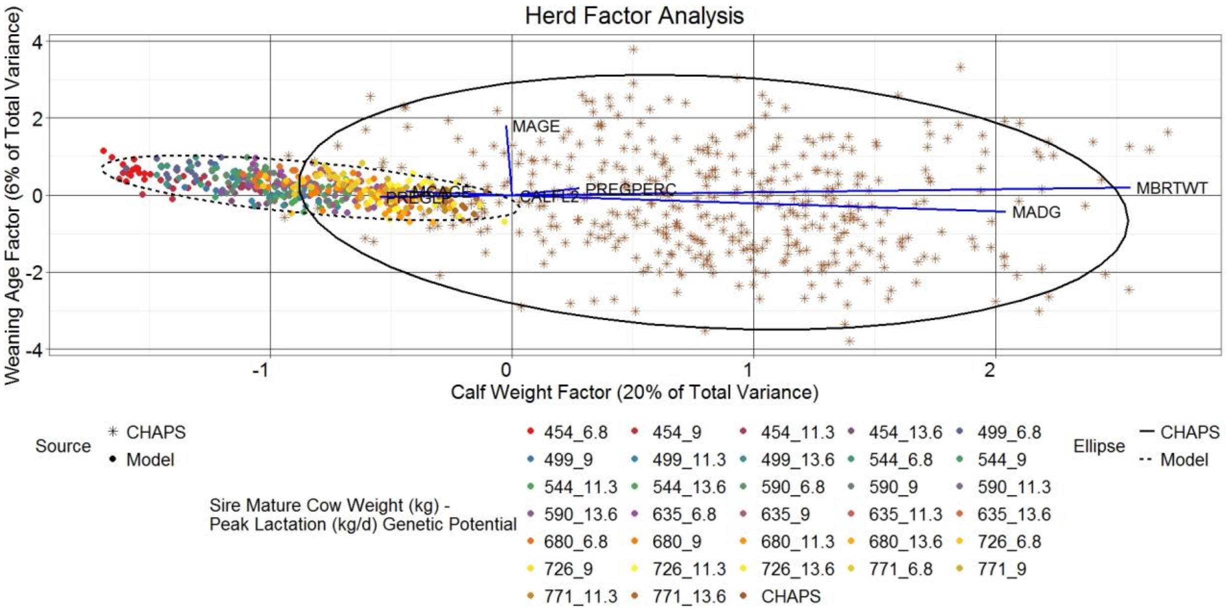

Figure 2.14. Yearly herd data factor score plot Weaning Age Factor by Calf Weight Factor. MBRTWT = mean actual calf birthweight, MAGE = mean calf weaning age, MADG = mean pre-weaning ADG, MCAGE = mean cow age, PREGPERC = percent pregnant per cow exposed, PREGLP = percent pregnancy loss per cow exposed, and CALFL2 = percent calf mortality per calf born. Blue lines represent variables' direction and magnitude of influence based on their factor loadings. Data ellipses represent the two sd factor score coordinate boundary

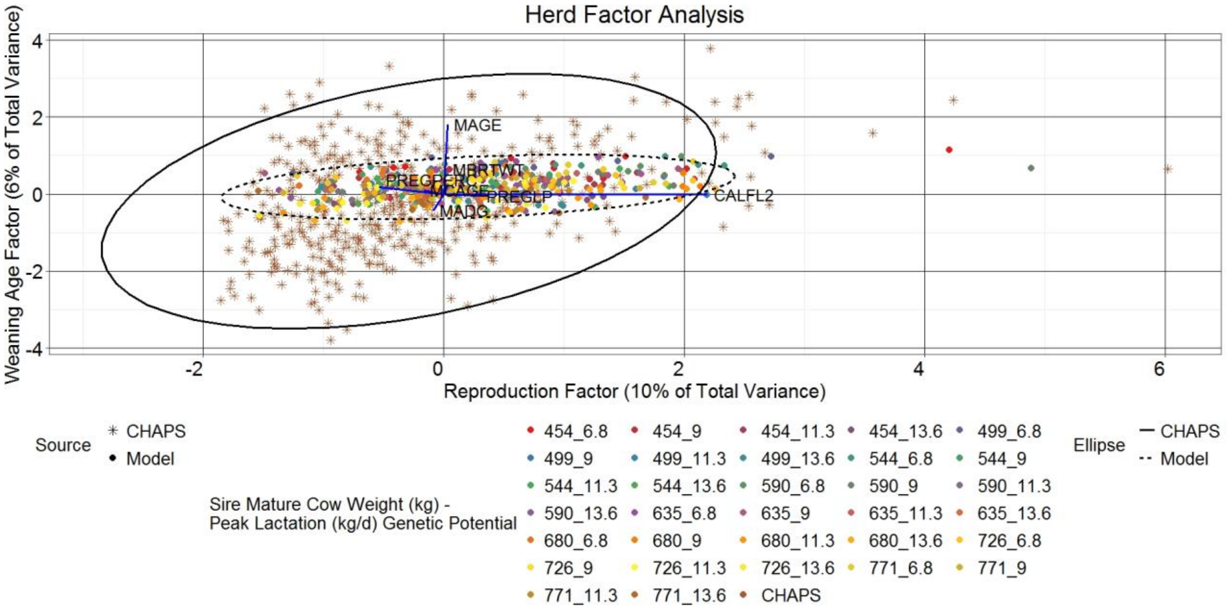

Figure 2.15. Yearly herd data score plot Weaning Age Factor by Reproduction Factor. MBRTWT = mean actual calf birthweight, MAGE = mean calf weaning age, MADG = mean pre-weaning ADG, MCAGE = mean cow age, PREGPERC = percent pregnant per cow exposed, PREGLP = percent pregnancy loss per cow exposed, and CALFL2 = percent calf mortality per calf born. Blue lines represent variables' direction and magnitude of influence based on their factor loadings. Data ellipses represent the two sd factor score coordinate boundary.

General

The stochastic, individual based systems simulation model described offers a unique opportunity to simultaneously account for genetics, nutrition, reproduction, growth, and health in beef cow-calf production settings. The model's stochastic elements consider the biological variation inherent to beef production which has tremendous advantages compared to deterministic techniques that ignore probabilistic risk and uncertainty. The systems design accounts for component interactions, as well as beef production's time delays and its complex, prolonged feedback structure. These capabilities make the model ideal for decision analysis through the assessment of a multitude of metrics simultaneously, over various time horizons. In addition, the model can be expanded to include stocker, backgrounder, and finishing phases of the beef production system.

At best, a model usefully simplifies reality’s complexity. The present model represents a mathematical interpretation of the current understanding regarding cow-calf production biology (i.e., a mathematical literature review). As such, any question a reader may have regarding model output validity or author assumptions may point to potential gaps in cow-calf production research; although opportunities for model improvements should not be ignored. The validation procedures applied support the real-world usefulness of model output, particularly from a scenario comparison perspective.

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Appendix 2.1: Model Parameters

Table 2.A1.1. Initialization parameters.

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
Iterations	Deterministic	100	User-defined	The number of iterations the user wishes to run an *i* production year simulation
Initial breeding herd size at calving	Deterministic	100	User-defined	
Breeding herd size goal	Deterministic	100	User-defined	The breeding herd size the user wishes to achieve.
Years to herd size	Deterministic	1	User-defined	The number of years the user wishes to pass in achieving the breeding herd size goal.
Initial heifer replacement rate	Deterministic	0.125	User-defined (default from Wittum et al.(1994), USDA (2010), Cushman et al. (2013), Ringwall (2014), and expert opinion)	
Breeding season start	Deterministic	May 1st	User-defined	
Breeding season end	Deterministic	July 3	User-defined	

Table 2.A1.2. Four-year rolling average Angus genetic trend for birth weight and weaning weight from 1992 to 2018.

Year	Angus Birth Weight EBV: Four Year Rolling Average	Angus Weaning Weight EBV: Four Year Rolling Average
1992	3.65	24.0
1993	3.80	27.0
1994	3.85	30.0
1995	3.80	32.5
1996	3.75	35.5
1997	3.75	38.0
1998	3.75	41.0
1999	3.80	44.5
2000	3.80	47.5
2001	3.80	51.0
2002	3.80	54.0
2003	3.80	57.0
2004	3.75	60.0
2005	3.7	62.5
2006	3.65	65.5
2007	3.55	68.5
2008	3.50	72.0
2009	3.40	75.5
2010	3.30	79.0
2011	3.20	82.0
2012	3.10	85.0
2013	3.00	88.0
2014	2.90	91.0
2015	2.85	94.5
2016	2.75	98.0
2017	2.70	102.0
2018	2.60	106.0

Adapted from AAA (2019b)

Table 2.A1.3. Genetic correlations.

Traits	Genetic Correlation	Reference
Weaning Weight: Mature Cow Weight	0.44	AAA (2019c)
Birth Weight: Weaning Weight	0.29	AAA (2019c)
Gestation: Birth Weight	0.30	Gregory et al. (1995)
Milk Production: Mature Cow Weight	0.14	Morris and Wilton (1976)

Table 2.A1.4. Manhattan, KS January through August Cumulative Precipitation.

Year	**Jan- Aug Cumulative Precipitation (in)**
1995	34.83
1996	23.61
1997	20.17
1998	24.15
1999	30.50
2000	15.43
2001	30.82
2002	18.43
2003	25.56
2004	32.54
2005	26.45
2006	26.2
2007	34.62
2008	33.07
2009	29.46
2010	26.70
2011	21.33
2012	17.46
2013	22.60
2014	23.88
2015	30.81
2016	31.01
2017	25.31
2018	19.98

From HPRCC (2019)

Table 2.A1.5. Grazing acre allocation for the eight scenario possibilities for mean mature cow weight.

Mean Mature Cow Weight (kg)	Full season grazing acres allocated per pair	Full season grazing acres allocated per yearling heifer	Grazing acres allocated per post-weaning replacement heifer
454	5.83	3.33	2.16
499	6.26	3.43	2.32
544	6.68	3.66	2.47
590	7.10	3.89	2.63
635	7.50	4.11	2.77
680	7.90	4.33	2.93
726	8.30	4.55	3.07
771	8.68	4.76	3.21

Table 2.A1.6. Ration nutrient densities by month.

Ration	**Month**	**NEm (Mcal/kg)**	**NEg (Mcal/kg)**	**DE (Mcal/kg)** (used for determining calf DMI)
Base (73% alfalfa, 19% wheat straw, and 8% corn)	Jan-Dec	1.2	0.64	NA
Supplement (60% alfalfa, 40% corn)	Jan-Dec	1.63	1.02	3.08
Bluestem Forage				
	Jan-Mar	0.71	0.18	1.89
	Apr-Jun	1.48	0.90	2.86
	Jul-Aug	1.10	0.54	2.12
	Sep-Dec	0.71	0.18	1.89

Calculated using estimates from NRC (2016) and Kuhl et al. (1993).

Table 2.A1.7. Assorted nutrition parameters.

Model Parameter	**Distribution Type**	**Distribution Parameters**	**Reference**	**Notes**
Percent of forage remaining at end of grazing season- goal	Deterministic	40%		
Metabolizable energy (Mcal) per kg of diet	Deterministic	2.0	NRC 2016	Assumed to be the same for all diets. Only a factor when calculating NEm requirements from gestation.

Table 2.A1.8. Daily maximum DMI as percent of SBW by MW category and animal production category.

Animal Category	Maximum Daily DMI (percent of SBW)
454 kg MW	
Post-weaning Non-pregnant Replacement Heifer	2.9
Bred Yearling Heifer	2.9
Two-Year-Old Cow	2.5
Three-Year-Old Cow	2.5
Mature Cow (>= 4-Years-Old)	2.4
499 kg MW	
Post-weaning Non-pregnant Replacement Heifer	2.9
Bred Yearling Heifer	2.7
Two-Year-Old Cow	2.4
Three-Year-Old Cow	2.4
Mature Cow (>= 4-Years-Old)	2.3
544 kg MW	
Post-weaning Non-pregnant Replacement Heifer	2.9
Bred Yearling Heifer	2.7
Two-Year-Old Cow	2.4
Three-Year-Old Cow	2.4
Mature Cow (>= 4-Years-Old)	2.3

Table 2.A1.9 (*cont.*) Daily maximum DMI as percent of SBW by MW category and animal production category.

Animal Category	Maximum Daily DMI (percent of SBW)
590 kg MW	
Post-weaning Non-pregnant Replacement Heifer	2.7
Bred Yearling Heifer	2.7
Two-Year-Old Cow	2.3
Three-Year-Old Cow	2.3
Mature Cow (>= 4-Years-Old)	2.2
635 kg MW	
Post-weaning Non-pregnant Replacement Heifer	2.7
Bred Yearling Heifer	2.7
Two-Year-Old Cow	2.3
Three-Year-Old Cow	2.3
Mature Cow (>= 4-Years-Old)	2.2
680 kg MW	
Post-weaning Non-pregnant Replacement Heifer	2.7
Bred Yearling Heifer	2.7
Two-Year-Old Cow	2.3
Three-Year-Old Cow	2.3
Mature Cow (>= 4-Years-Old)	2.2

Table 2.A1.10 (*cont.*) Daily maximum DMI as percent of SBW by MW category and animal production category.

Animal Category	Maximum Daily DMI (percent of SBW)
726 kg MW	
Post-weaning Non-pregnant Replacement Heifer	2.7
Bred Yearling Heifer	2.7
Two-Year-Old Cow	2.2
Three-Year-Old Cow	2.2
Mature Cow (>= 4-Years-Old)	2.1
771 kg MW	
Post-weaning Non-pregnant Replacement Heifer	2.7
Bred Yearling Heifer	2.7
Two-Year-Old Cow	2.2
Three-Year-Old Cow	2.2
Mature Cow (>= 4-Years-Old)	2.1

Table 2.A1.11. BCS and corresponding body fat composition, percent of MSBW, and Mcal per kilogram of EBW loss and EBW gain.

BCS	Percent Body Fat EBW Composition	Percent of MSBW (BCS 5)	Mcal per kg EBW Loss	Mcal per kg EBW Gain
1	3.77	71.6	3.69	4.22
2	7.54	78.7	4.22	4.76
3	11.30	85.8	4.76	5.30
4	15.07	92.9	5.30	5.84
5	18.89	100.0	5.84	6.38
6	22.61	107.1	6.38	6.91
7	26.38	114.2	6.91	7.45
8	30.15	121.3	7.45	7.99
9	33.91	128.4	7.99	8.60

Adapted from NRC (2016)

Table 2.A1.12. Maximum base fed ration intake by animal production category.

Animal Production Category	**Maximum Base Fed Ration Intake (kg/d)**
Nursing Calf*	7.0
Post-weaning Non-pregnant Replacement Heifer	13.0
Bred Yearling Heifer	13.0
Two-Year-Old Cow	16.0
Three-Year-Old Cow	16.0
Mature Cow (>= 4-Years-Old)	16.0

*Base Fed Ration for Nursing Calves is equivalent to Supplement Ration for all other animal categories

Table 2.A1.13. Reproductive cyclicity.

Model Parameter	**Distribution Type**	**Distribution Parameters**	**Reference**	**Notes**
Postpartum Interval (d)- Primiparous Cows			Ciccioli et al. (2003), Berardinelli et al. (2005), Endecott et al. (2007), and expert opinion	
BCS 1	Pert	(350, 350, 350)		
BCS 2	Pert	(135, 150, 165)		
BCS 3	Pert	(85, 100, 115)		
BCS 4	Pert	(65, 80, 95)		
BCS 5	Pert	(55, 70, 85)		
BCS 6	Pert	(45, 60, 75)		
BCS 7	Pert	(30, 45, 60)		
BCS 8	Pert	(30, 45, 60)		
BCS 9	Pert	(30, 45, 60)		

Table 2.A1.14 (*cont*). Reproductive cyclicity.

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
PostPartum Interval (d)- Multiparous Cows			Graham (1982),Rutter and Randel (1984), Houghton et al. (1990), Cushman et al. (2007), Lents et al. (2008), and expert opinion	
BCS 1	Pert	(350, 350, 350)		
BCS 2	Pert	(135, 150, 165)		
BCS 3	Pert	(75, 90, 105)		
BCS 4	Pert	(55, 70, 85)		
BCS 5	Pert	(45, 60, 75)		
BCS 6	Pert	(35, 50, 65)		
BCS 7	Pert	(30, 35, 50)		
BCS 8	Pert	(30, 35, 50)		
BCS 9	Pert	(30, 35, 50)		
Dystocia Probability per Parturition			McDermott et al. (1990), USDA (2008), and expert opinion	
Multiparous Cow	Normal	(0.05, 0.01, lower=0)		
Primiparous Cow- Calf birthweight < 40.82 kg	Normal	(0.08, 0.01, lower=0)		
Primiparous Cow- Calf birthweight >= 40.82 kg	Normal	(0.5, 0.01, lower=0)		

Table 2.A1.15 (*cont*). Reproductive cyclicity.

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
Additional PPI (d) resulting from dystocia	Normal	(10, 2, lower=0)	Doornbos et al. (1984), Bellows et al. (1988), and expert opinion.	
Pregnancy probability at d equal to estrous cycle length after breeding			Spell et al. (2001), Chagas et al. (2002), Aherin et al. (2018), and expert opinion	
Heifers	Normal	(0.71, 0.01, upper = 0.8)	Cundiff et al. (1974)	
Primiparous Cows	Normal	(0.61, 0.01, upper=0.8)	Cundiff et al. (1974)	
Multiparous Cows	Normal	(0.71, 0.01, upper = 0.8)	Cundiff et al. (1974)	
Pregnancy Loss				

Table 2.A1.16 (*cont*). Reproductive cyclicity.

Model Parameter	**Distribution Type**	**Distribution Parameters**	**Reference**	**Notes**
Daily mean probability of returning to cyclicity after establishing pregnancy				
d 25 to d 45	Normal	(0.002, 0.0002, lower = 0)	Whittier et al. (1991), Lamb et al. (2008), Aherin et al. (2018), and expert opinion.	
d 46 to d 65	Normal	(0.0005, 0.00002, lower = 0)	Whittier et al. (1991), Lamb et al. (2008), Aherin et al. (2018), and expert opinion.	
d > 65	Normal	(0.0001, 0.00002, lower = 0)	Dziuk and Bellows (1983), van Wagtendonk-de Leeuw et al. (2000), Aherin et al. (2018), and expert opinion	
Gestation length	Normal	(285, 7)	Expert opinion	The length of each individual gestation is randomly determined by drawing from a normal distribution.

Table 2.A1.17. Culling.

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
Pregnancy determination (days after breeding season end)	Deterministic	60	User-defined	
Age (d) of oldest calf at weaning	Deterministic	220	User-defined	
Maximum cow age	Deterministic	13	User-defined	
Minimum culling percentage by cow age (years) (involuntary and voluntary combined)			Wittum et al.(1994), USDA (2010), Cushman et al. (2013), Ringwall (2014), and expert opinion	culls within age/exposed within age
1	Deterministic	5%		
2	Deterministic	10%		
3	Deterministic	6%		
4	Deterministic	6%		
5	Deterministic	6%		
6	Deterministic	6%		
7	Deterministic	6%		
8	Deterministic	6%		
9	Deterministic	8%		
10	Deterministic	10%		
11	Deterministic	40%		
12	Deterministic	50%		
13	Deterministic	100%		

Table 2.A1.18. Morbidity and mortality.

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
Daily probability of preweaned calf morbidity			Wittum et al. (1994), Sanderson and Dargatz (2000), USDA (2010), and expert opinion	
Dystocia and neonatal period (d 1-3 after parturition)	Normal	(0.01, 0.005, lower=0)		
No dystocia and neonatal period (d 1-3 after parturition)	Normal	(0.005, 0.001, lower=0)		
Dystocia and post-neonatal period to weaning	Normal	(0.0004, 0.00001, lower=0)		
No dystocia and post-neonatal period to weaning	Normal	(0.0002, 0.00001, lower=0)		

Table 2.A1.19 (*cont*). Morbidity and mortality.

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
Daily probability of preweaned calf mortality			Laster and Gregory (1973), Patterson et al. (1987), Wittum et al. (1994), USDA (2010), and expert opinion	
Dystocia, no morbidity, and neonatal period	Normal	(0.06, 0.005, lower=0)		
Dystocia, morbidity, and neonatal period	Normal	(0.1, 0.0005, lower=0)		
No dystocia, no morbidity, and neonatal period	Normal	(0.01, 0.001, lower=0)		
No dystocia, morbidity, and neonatal period	Normal	(0.05, 0.001, lower=0)		
Dystocia, no morbidity, and post-neonatal period to weaning	Normal	(0.0001, 0.00001, lower=0)		
Dystocia, morbidity, and post-neonatal period to weaning	Normal	(0.001, 0.0001, lower=0)		
No dystocia, no morbidity, and post-neonatal period to weaning	Normal	(0.0001, 0.00001, lower=0)		
No dystocia, morbidity, and post-neonatal period to weaning	Normal	(0.0005, 0.0001, lower=0)		

Table 2.A1.20 (*cont*). Morbidity and mortality.

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
Daily probability of postweaning mortality			USDA (2010), and expert opinion	
Dystocia at birth	Normal	(0.00005, 0.00001,lower =0)		
No Dystocia at birth	Normal	(0.000025, 0.00001,lower =0)		
Daily probability of mature mortality	Normal	(0.000025, 0.00001,lower =0)	USDA (2010), and expert opinion	
Percent reduction in WW from morbidity	Normal	(0.065, 0.0065)	Wittum et al. (1994)	Applied to each calf individually

Table 2.A1.21. Calf growth**.**

Model Parameter	**Distribution Type**	**Distribution Parameters**	**Reference**	**Notes**
Calf birthweights				
Bull calf, two-year-old dam mean birthweight adjustment (kg)	Deterministic	-3.63	BIF (2010)	
Bull calf, three-year-old dam mean birthweight adjustment (kg)	Deterministic	-2.27	BIF (2010)	
Bull calf, four-year-old dam mean birthweight adjustment (kg)	Deterministic	-0.91	BIF (2010)	
Bull calf, eleven-year-old and older dam mean birthweight adjustment (kg)	Deterministic	-1.36	BIF (2010)	

Table 2.A1.22. Calf growth**.**

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
Calf birthweights				
Heifer calf, two-year-old dam mean birthweight adjustment (kg)	Deterministic	-3.17	BIF (2010)	
Heifer calf, three-year-old dam mean birthweight adjustment (kg)	Deterministic	-2.27	BIF (2010)	
Heifer calf, four-year-old dam mean birthweight adjustment (kg)	Deterministic	-0.91	BIF (2010)	
Heifer calf, eleven-year-old and older dam mean birthweight adjustment (kg)	Deterministic	-1.36	BIF (2010)	

Chapter 3 - Stochastic systems model assessment of cow-calf biological and economic efficiency for different mature weight and peak lactation combinations in the Kansas Flint Hills

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Abstract

In cow-calf production, biological and economic efficiency are not perfectly synonymous. Research simultaneously assessing both the biological and economic efficiency of different mature cow weight and peak lactation combinations for twenty-first century cow-calf production is scarce to non-existent. A stochastic, individual based systems simulation model was parameterized to match Kansas Flint Hills production and economic conditions for the years 1995 through 2018. Eight sire mature cow weight (MW) genetic potentials ranging from 454 kg to 771 kg in 45 to 46 kg increments were combined with four different sire peak lactation (PL) genetic potentials (6.8, 9, 11.3, and 13.6 kg/d) to generate 32

distinct breeding system scenarios. The model was simulated 100 iterations for each of the 32 scenario herds.

Aggregating simulation results for the 2000 through 2018 production years, under the specific parameters previously described, larger, heavier milking cows excelled in kilograms weaned per cow exposed, while kilograms weaned per net energy for maintenance (kg/Mcal*100) favored smaller, heavier milking cows. Assuming no price differentiation between weaned calves from different breeding systems, 454 and 499 kg mature cow weight with 13.6 kg/d peak lactation had the highest median annual enterprise return on investment (fed ration, pasture, replacement, and interest expenses) at 8.9 and 7.4 percent, respectively. Applying the assumptions that herds comprised of 454 and 499 kg mature cow weight with 13.6 kg/d peak lactation do not exist and that all weaned calves from 454 kg mature cow weight breeding systems receive a small frame price discount, the 544 kg mature cow weight-13.6 kg/d peak lactation combination generated the greatest median annual return on investment at 7.0 percent. Several combinations of 499, 544, 590, and 635 kg mature cow weights with 11.3 or 13.6 kg/d peak lactation produced a median annual return on investment between 4.1 percent and 5.4 percent.

Introduction

The conversation surrounding cow-calf production efficiency in the modern beef industry structure has been ongoing since the establishment of a specialized cattle feeding sector and the import of Continental breeds laid the foundation for the modern era in the 1960s and 1970s (Dickerson, 1970; Ritchie and Hawkins, 1984). Despite the research and thought invested in the discussion, two primary factors have likely prohibited a general industry consensus on defining the efficient beef cow:

(1) Production and economic environments varying across time and geography, along with differing management practices and marketing strategies dictate that optimal beef cow traits fluctuate between operations.

(2) Biological efficiency and economic efficiency are not perfectly synonymous.

A quick study surrounding the diversity of beef production systems, breeding objectives, fluctuating input costs, and the cattle cycle itself forces one to recognize that the optimal beef cow is a moving target and one size does not fit all. The relationship between biological and economic efficiency warrants further investigation.

Biological Efficiency

Biological efficiency through weaning has been measured in a multitude of ways. Typically, metrics are some ratio between calf weight weaned, cows exposed for breeding, cow weight, feed weight input, and feed energy input, or a combination thereof. Generally, the goal is to compare the output (calf weight weaned) to some estimation of energy input, albeit some denominators are more direct than others (feed energy input vs cow weight). Johnson (1984) calculated that of the total dietary energy required for beef production, 71%

is applied to maintenance and 70% of the total maintenance energy is used by the cow herd. Thus, 50% of beef production's dietary energy consumption is devoted to the breeding herd (Ritchie, 2001). Critical to assessing cow maintenance energy and efficiency are cow weight and lactation (Arango and Van Vleck, 2002).

Mature cow weights have increased since the 1970s. McMurry (2009) estimated an increase in the US average mature beef cow weight from 1050 pounds to 1350 pounds between 1975 and 2009. Given the genetic correlations between growth and mature weight (AAA, 2019b), this increase is likely due to selection pressure on growth and other output traits.

When considering Kleiber's Theory (metabolic weight = live weight^0.75) (Kleiber, 1932), the math emphasizes more efficient energy use by larger animals. Johnson et al. (2010) provides an extreme comparison by highlighting that an elephant weighing 220,000 times more than the average mouse only requires 10,000 times the dietary energy for maintenance. Put in cattle terms, a 1200 pound cow weighing 20% more than her 1000 pound counterpart only requires 13% more maintenance energy (Johnson et al., 2010). What this train of thought fails to consider is the reduced reproductive rate in larger cows, if the increased nutrient demands of those larger cows are not met (Johnson et al., 2010). It is well documented that inferior reproduction quickly eliminates any efficiency advantage that may have resulted from differences in growth or feed consumption (Jenkins and Ferrell, 2002).

Jenkins and Ferrell (1994) captured the preceding concept in a study of efficiency (grams calf weaned/kilograms dry matter intake/cow exposed) across nine breeds and varying dry matter intake (DMI). At low DMI levels the smaller, lighter milking breeds ranked higher in efficiency. The larger, heavier milking breeds ranked higher in efficiency than their smaller, lighter milking counterparts as DMI increased, and the nutrient demands of the breeds with more production potential were met.

Using production data from high-elevation, semi-arid rangeland in Wyoming, Scasta et al. (2015) measured efficiency as percent of cow body weight weaned across five mature cow weights. The researchers found that smaller cows were more efficient than larger cows, but the advantage decreased substantially in extreme drought years. Perhaps under extreme drought conditions the nutritional challenge to all cow sizes surpassed some production limiting threshold.

Montano-Bermudez et al. (1990) attributed an estimated 23% of the variation in maintenance requirement per kg metabolic weight to milk production. The researchers also found that cows in the High and Medium milking groups required 12% more energy per kg metabolic weight than the Low milking group, even when not lactating, supporting Ferrell and Jenkins (1984) and Taylor et al. (1986). The difference in non-lactating maintenance requirement for animals with greater lactation potential has been attributed to increased internal organ mass and the subsequent demand for more nutrients (Burrin et al., 1990; Canas et al., 1982; Ferrell and Jenkins, 1984).

Economic Efficiency

Reproduction drives profitability at the cow-calf level (MacNeil et al., 1994; Melton, 1994). Melton (1994) calculated that weaning rate accounts for 73% of cow-calf production’s economic value. After adjusting for trait means, variance, heritability, and inter-trait correlations, Melton (1994) concluded that the profit maximizing cow-calf firm places 47% of all selection emphasis on reproductive traits.

Similar to Jenkins and Ferrell (1994)'s finding that biological efficiency may re-rank depending on nutrient constraints, both Smith et al. (1987a,b) and Armstrong et al. (1990) demonstrated that economic efficiency of different biological cattle types may re-rank depending on resource restrictions or management constraints (Ritchie, 2001). Armstrong et al. (1990) specifically noted re-ranking in net return in favor of smaller, lighter milking cows when nutritional restriction placed more reproductive stress on larger, heavier milking cows.

Upon stochastically modeling a 10-year production history for five different biological beef cattle types and accounting for heterosis effects, Davis et al. (1994) demonstrated that net return rankings, and return on investment calculated from reported financial outcomes (net return per cow exposed/total cost per cow exposed), did not match energy conversion rankings (megacalories of metabolizable energy/kg calf weight weaned). Davis et al. (1994) also found that economic efficiency favored moderate output crossbred females.

Using a budget analysis for both native and improved pasture in the southern plains, Doye and Lalman (2011) concluded that while 1400 pound cows generated more gross income per cow, 1100 pound cows yielded greater net return per cow. They also calculated that 1100 pound cows generated greater net return on a fixed land use basis.

Additional economic analyses on actual cow-calf production data have been conducted in more recent years. Beck et al. (2016) compared 4 years (2009-2012) of actual production data between 571 kg mean body weight cows and 463 kg mean body weight cows at four different stocking rates in southwestern Arkansas. While calf weaning weight increased by 19 kg per 100 kg increase in cow body weight ($p<0.01$), the 88% average pregnancy percentage across the four years was unaffected by mature cow body weight or stocking rate. Under the study's specific environment, management practices, and economic conditions, Beck et al. (2016) reported that per hectare and per cow profitability was unaffected by cow body weight. Net return per hectare increased as cows stocked per hectare increased ($p<0.01$). Gillen and Sims et al. (2002) found that net return per acre decreased if stocking rate was increased past its optimal level and the variability in both biological and economic outcomes increased with stocking rate increases.

Bir et al. (2018) applied deterministic, regression based procedures to assess net present value (NPV) per acre across an entire cattle cycle with varying mature cow size using production data from two Oklahoma and one Arkansas research herds. Mature cow weight ranging from 950 pounds to 1800 pounds in 50 pound increments were evaluated under 8 different combinations of Angus or Brangus breed type; fall or spring calving; and native or Bermuda pasture. In all cases, 950 pound cows maximized NPV per acre. The researchers attributed this finding to higher stocking rate parameters for smaller cows, weaned calf price slides, and a nonlinear increase in calf weaning weight related to increased mature cow weight (Bir et al., 2018).

In an assessment of net return to different management and marketing scenarios through regression techniques applied to four years of production data from the Nebraska Sandhills, Stockton et al. (2016) found that lighter cow weights maximized net return per cow when calves were sold at weaning or as yearlings. When calf ownership was retained through the feeding phase, the researchers reported that heavier cows maximized net return per cow. Stockton et al. (2016) emphasizes the need to continue discussion regarding economically optimal cow size and expand systems research into the complex interrelation between beef production phases.

While net return and NPV per acre serve vital roles in assessing profitability and efficiency from a land use perspective, complementary measures such as internal rate of return or return on investment are needed to assess the efficiency of dollars invested. Neither net return nor NPV account for the required investment expenses needed to generate return (NPV simply accounts for the time value of money by discounting a series of net returns in the form of cash flows). For example, two investments with identical rates of return could have vastly different NPVs, if vastly different dollar amounts are invested. Thus, it is possible that return on investment decreases while NPV per acre increases, if non-land costs per dollar returned increase significantly as stocking rate increases.

Systems Modeling

Johnson et al. (2010) notes that identifying profit maximizing production strategies for a given production scenario requires an understanding of the interrelated components of efficiency. Systems thinking focuses on the interpretation of how different components of a system interact with one another and how an action or change in one component affects the entire system, either directly or through potential feedback structures (Sterman, 2000). Systems dynamics combines systems thinking with mathematical modeling to create tools for learning about complex systems (Sterman, 2000). Hirooka (2010) and Chapter 2-Introduction elaborate on the past applications and future opportunities of systems modeling in the beef industry.

Objectives

Both Doye and Lalman (2011) and Bir et al. (2018) comment on the limited research regarding the economic efficiency of beef production, not to mention the scarcity of studies that simultaneously assess the biological and economic efficiency under the same production setting. The objective of the present study was to apply the stochastic, systems model described in Aherin et al. (2020) to quantify both the biological and economic efficiency of cow-calf production from the year 2000 to 2018 between varying combinations of mature cow weight and peak lactation in the Kansas Flint Hills.

Materials and Methods

To achieve the stated objective, beef production literature, raw data, and expert opinion encompassing nutrition, reproduction, genetics, health, and historical feed and cattle prices are synthesized into an individual animal based, stochastic, cow-calf production system simulation model as described in Aherin et al. (2020). Eight sire mature cow weight (MW) genetic potentials ranging from 454 kg to 771 kg in 45 to 46 kg increments are combined with four different sire peak lactation (PL) genetic potentials (6.8, 9, 11.3, and 13.6 kg/d) to generate 32 distinct breeding system scenarios.

Model Simulation

The model was simulated 100 iterations (Chapter 2- Materials and Methods) for each of the 32 scenario herds. Each iteration ran for 24 production years (1995-2018). The length (d) of a model "production year" varied for each cow as it was defined as the time from calving in year *i* to either calving in year *i*+1 or culling for each individual breeding female. A "production year" for non-pregnant replacement females was the days from birth to first conception or the end of the breeding season, if a female did not conceive. Results for 1995 through 1999 are not reported in order to facilitate the stabilization of initial exogenous parameters (Chapter 2- Materials and Methods).

Monthly average temperature, relevant to animal maintenance requirements, and monthly precipitation data (Appendix 3.1: Table 3.A1.5), applied to a forage production model (Chapter 2- Materials and Methods), for Manhattan, KS were obtained from HPRCC (2019) to parameterize a production environment similar to the Kansas Flint Hills. The modeled grazing season spanned from May 1 to October 31 (KSU and KDA, 2019) with acre allocation adjusted for MW on a per head basis according to Chapter 2- Materials and Methods (Appendix 3.1: Table 3.A1.6). In addition, historical feed ingredient prices, pasture rental costs, cattle prices, and effective interest rates were matched as available to the Flint Hills region or the state of Kansas.

Non-pregnant replacement heifer calves were retained with the goal to expose 100 females during each May 1 through July 3 (63 d) breeding season. Sixty days after the end of the breeding season, pregnancy status was determined for all exposed females. All non-pregnant females and all 13-year-old cows were culled on the weaning date. Chapter 2- Materials and Methods describes additional culling rules replicating voluntary culling for each female age group. Females that abort a pregnancy after the weaning date are culled on the abortion day. Weaning occurred when the oldest calf reach 220 d old. All calves were sold on the weaning date. If the number of non-pregnant replacement heifers required per Chapter 2- Materials and Methods to maintain herd size exceeded the number of heifers raised, additional heifers were purchased with similar genetics to the raised heifer population.

One hundred percent Angus genetic makeup was assumed with the genetic trend for sire birth weight (BW) EBVs and sire weaning weight (WW) EBVs following breed average for a given birth year (Chapter 2- Materials and Methods). Each animal had a genetic potential for BW, WW, MW, and PL according to mating averages and Mendelian sampling rules as described in Chapter 2- Materials and Methods.

With scenario comparison as the primary interest and an identical breeding herd goal for each scenario, any bull derived scenario differences should be minor. Therefore, bulls were not included in the model.

Appendix 3.1 reports further model parameter information. See Chapter 2- Materials and Methods for additional details regarding model design and specifications related to genetics, nutrition, reproduction, and health, as well as model validation procedures.

Economics

Effective annual interest rates across all non-real estate agricultural loans for each year from 1995-2018 were input into the model to account for the cost of cash needed to cover fed ration, pasture, and replacement expenses (FED, 2019; Appendix 3.1: Table 3.A1.17).

Monthly average steer prices by weight class (pounds) (<=500, >500 to 600, >600 to 700, >700 to 800, >800 to 900, >900) and monthly heifer prices by weight class (pounds) (<=500, >500 to 600, >600 to 700, >700 to 800, >800) from January 2000 through November 2019 were retrieved from the Livestock Marketing Information Center (LMIC) “CombinedAuctionsKS” spreadsheet (LMIC, 2019). Monthly average 85-90% lean cull cow price from January 2000 through November 2019 were also retrieved from LMIC’s “wkancatl” spreadsheet (LMIC, 2019).

Average monthly corn price (USD per bushel) and ground alfalfa hay price (USD per ton) as reported from February 1990 to September 2019 in the “K-State Focus on Feedlots”

(KSU ASI, 2019) retrieved from LMIC (LMIC, 2019) were used to estimate monthly ration costs. Wheat straw price (USD per ton) was assumed to be 50% of alfalfa hay price.

The Kansas Bluestem Pasture Survey (Dhuyvetter et al., 2009; KSU and KDA, 2017; KSU and KDA, 2019) was used to account for pasture rental costs. The yearly combined (with and without care) rental cost per head for each of the surveyed cattle type categories (1250 pound cow-calf pairs, under 700 pounds, and over 700 pounds) for each year from 1995 through 2018 as reported by Dhuyvetter et al. (2009), KSU and KDA (2017), and KSU and KDA (2019) were collected. Because of the rarity of measured mature cow weights and tendencies for inaccurate visual weight estimation, it was assumed the "1250 pound cow-calf pair" category represented the average cow rather than a specific mature cow weight class. The years with missing combined (with and without care) average per head rental costs (2005, 2010-2012, 2014, 2016, 2018, and 2019) were estimated based on the surrounding years. The reported acre allocation for each respective cattle type category and each year from 1995-2018 was averaged for each cattle type category to determine an across time average. The years with missing data points for acreage allocation were ignored. For each cattle type category, the combined average per head rental cost for each year was then divided by the across time average acreage allocation to determine a yearly average rental cost per acre to input into the model (Appendix 3.1: Table 3.A1.7). Only the years 2000-2018 were considered for the present study.

Return over Fed Ration, Pasture, Replacement, and Interest Expense

According to the 2018 and 2019 KSU Beef- Farm Management Guide Budgets, roughly 65% of cow-calf variable costs stem from fed ration, pasture, and replacement costs (Reid and Tonsor, 2018; Reid and Tonsor, 2019). Given the variation across enterprises resulting from diverse technology use and geographic spread, labor, fuel, utilities, facilities, and equipment costs are not included in the scope of this study. In order to narrow the comparative focus on the costs most directly associated with cow type, only fed ration, pasture, replacement expenses and the interest charge on said expenses were assessed within the present study.

Income is derived from the sale of weaned calves and cull cows. All calves are valued individually at weaning based on their actual weight and the price associated with their sex, weight class, and marketing month. Cull cows are valued based on their actual weight, which is calculated daily, and the month in which they are sold. All cull cows within a given month receive the same price per pound, regardless of weight. The sum of the individual values for all weaned calves and cull cows represents gross revenue for a given production year.

Replacement heifers are valued individually at weaning as described previously for all calves. Daily fed ration costs for both the base and supplement ration are calculated individually for all animals based on monthly ration ingredient prices. Daily fed ration costs are summed for individuals and then summed across all animals to determine total fed ration expense for a given production year. Pasture cost is determined according to the number of animals in each cattle type, the acre allocation per head for the relevant cattle type, and the price per acre. It is assumed that 100% of all considered expenses (fed ration, pasture, and replacements) are financed through a loan repaid with a lump sum in one year.

All input and output prices, excluding interest rate, are multiplied by a stochastic factor randomly drawn from a normal distribution (mean=1) for each iteration to account for the variation across individual operations (Appendix 3.1: Table 3.A1.4). Theoretically, this variation may result from input source or cattle reputation.

Financial Equations

Revenue

Weaned steer revenue for production year *i* equals

$$WSR_i = \Sigma_{j=1}^{WS_i} WW_j * PS_j$$

where

WSR_i = weaned steer value for production year *i*,
WS_i = total number of steers weaned in production year *i*,
WW_j = steer *j* weaning weight, and
PS_j = price per pound for steer *j* given year, month, and weight class.

Weaned heifer revenue for production year *i* equals

$$WHR_i = \Sigma_{j=1}^{WH_i} WW_j * PH_j$$

where

WHR_i = total weaned heifer value for production year *i*,
WH_i = total number of weaned heifers in production year *i*,
WW_j = heifer *j* weaning weight, and
PH_j = price per pound for heifer *j* given year, month, and weight class.

Cull cow revenue for production year *i* equals

$$CCR_i = \Sigma_{j=1}^{C_i} CW_j * PC_j$$

where

CCR_i = cull cow value for production year *i*,
C_i = total number of breeding females culled in production year *i*,
CW_j = cull cow *j* weight, and
PC_j = price per pound for cull cow *j* given year and month.

Total revenue for production year *i* equals

$$TR_i = WSR_i + WHR_i + CCR_i$$

where

TR_i = total weaned steer, weaned heifer, and cull cow value for production year *i*.

Expense

Total fed ration expense for production year *i* equals

$$TFR_i = \Sigma_{j=1}^{X_i} \Sigma_{d=1}^{Y_j} (B_{dj} + S_{dj})$$

, where:
TFR_i = total fed ration expense for production year *i*,
X = total number of animals alive for at least one day during production year *i*,
B_{dj} = base ration expense for animal *j* on day *d*, and
S_{dj} = supplement ration expense for animal *j* on day *d*.

Total cow-calf pair pasture expense for production year *i* equals

$$PCC_i = CC_i * A_C * R_{Ci}$$

where:

PCC_i = total cow-calf pair pasture expense for production year *i*,
CC_i = total number of cow-calf pairs at the start of the grazing season for production year *i*,
A_c = acreage allocation per cow-calf pair, and
R_{Ci} = full summer grazing pasture expense per acre for a cow-calf pair in production year *i*.

Total post-weaning replacement pasture expense for production year *i* equals

$$PPR_i = RR_i * A_P * R_{Pi}$$

where:

PPR_i = total post-weaning replacement pasture expense for production year *i*,
RR_i = total number of replacements required in production year *i*,
A_P = acreage allocation per post-weaning replacement female, and
R_{Pi} = partial season grazing pasture expense per acre for post-weaning replacement females in production year *i*.

Total yearling heifer pasture expense for production year *i* equals

$$PYH_i = YH_i * A_H * R_{Hi}$$

where:

PYH_i = total yearling heifer pasture expense for production year *i*,
YH_i = total number of yearling heifers at start of grazing season in production year *i*,
A_H = acreage allocation per yearling heifer, and

R_{Hi} = full summer grazing pasture expense per acre for yearling heifers in production year i.

Total pasture expense for production year *i* equals

$TPR_i = PCC_i + PPR_i + PYH_i$.

Total replacement heifer value for production year i equals

$$RV_i = \Sigma_{j=1}^{RR_i} WW_j * PH_j$$

where

RV_i = total replacement heifer value for production year *i*,
RR_i = total number of replacement required in production year *i*,
WW_j = heifer *j* weaning weight, and
PH_j = price per pound for heifer *j* given year, month, and weight class.

Interest expense for production year *i* equals

$$I_i = (TFR_i + TPR_i + RV_i) * r_i$$

where

I_i = total interest expense for production year *i*, and
r_i = effective interest rate for production year *i*.

Total expense for production year *i* equals

$$TE_i = TFR_i + TPR_i + RV_i + I_i$$

where

TE_i = total fed ration, pasture, replacement, and interest expense for production year *i*.

Net Return

Total net return for production year *i* equals

$$NR_i = TR_i - TE_i$$

where

NR_i = total net return over fed ration, pasture, replacement, and interest expense for production year *i*.

Efficiency Metrics

Two biological and three economic efficiency metrics were calculated from model output.

Standardized Performance Analysis- Kg Weaned per Cow Exposed

$$KPC\ SPA_i = \frac{Total\ Actual\ Calf\ Kilograms\ Weaned_i}{Breeding\ Females\ Exposed_{i-1} - Pregnant\ Culls_{i-1}}$$

where

$KPC\ SPA_i$ = standardized performance analysis- kg weaned per cow exposed for production year i,

$Total\ Actual\ Calf\ Kilograms\ Weaned_i$ = sum of unadjusted weaning weight (kg) for all weaned calves in production year i,

$Breeding\ Females\ Exposed_{i-1}$ = total number of females exposed during the breeding season in production year i-1, and

$Pregnant\ Culls_{i-1}$ = total number of pregnant females that were cull during production year i-1.

Kilograms Weaned per Net Energy for Maintenance, Gestation, and Lactation Intake

$$KW\ Hundred\ NEm_i = \left(\frac{Total\ Actual\ Calf\ Kilograms\ Weaned_i}{Whole\ System\ NEm\ Intake_i}\right) * 100$$

$$KW\ NEm_i = \frac{Whole\ System\ NEm\ Intake_i}{Total\ Actual\ Calf\ Kilograms\ Weaned_i}$$

where

$KW\ NEm_i$ = Net energy for maintenance, gestation, and lactation (NEm) intake per kilogram weaned in production year i, and

Whole System NEm Intake$_i$ = sum of NEm intake for all animals (calves, replacements, and cows) in production year *i*.

Return per Breeding Female

$$Return\ per\ Breeding\ Female_i = \frac{NR_i}{Breeding\ Females\ Exposed_i}$$

where:

Return per Breeding Female$_i$ = dollars returned per breeding female in production year *i*, and

Breeding Females Exposed$_i$ = total number of females exposed during the breeding season in production year *i*.

Return per Grazing Acre

$$Return\ per\ Grazing\ Acre_i = \frac{NR_i}{Total\ Grazing\ Acres_i}$$

where

Return per Grazing Acre$_i$ = dollars returned per grazing acre in production year *i*, and

Total Grazing Acres$_i$ = sum of grazing acres allocated for cow-calf pairs, yearling heifers, and replacement heifer calves during production year *i*.

Return on Investment

$$ROI_i = \frac{NR_i}{TE_i}$$

where

ROI$_i$ = dollar return per dollar expense for production year *i*.

Results and Discussion

Biological Efficiency

Standardized Performance Analysis- Kg Weaned per Cow Exposed

Summarized across all simulation iterations and all 19 production years (i.e., over the long run), kilograms weaned per cow exposed (KPC), adjusted for pregnant culls according to Standardized Performance Analysis (SPA) guidelines, increased with increasing MW category and increasing PL category (Fig. 3.1). These results are not surprising given the modeled scenarios in which decision rules dictate that individual breeding female nutrient requirements are met as closely as possible, thus supplementation occurs as individually required. Under such conditions, model results show little difference in percent pregnant at diagnosis (PPD) across years or cow type (Appendix 3.2: Fig. 3.A2.1).

The increase in KPC SPA with increased MW category stems from the base genetic WW equation (prior to Mendelian sampling, genetic correlation, and calf nutrient considerations) in which a 100 kg deviation from 635 kg MW base causes a 12.5 kg directionally similar change in WW potential. Despite the linear equation for base genetic WW potential, actual WW response to increasing MW category was slightly nonlinear when all PL categories were aggregated within MW category (Appendix 3.2: Table 3.A2.1). Bir et al. (2018) also reported a nonlinear response in weaning weight per calf to changing cow weight. Given consistent reproductive rates and weaning age (Appendix 3.2: Fig. 3.A2.2) in the present study, differences in KPC SPA can be largely attributed to actual WW per calf differences (Appendix 3.2: Fig. 3.A2.6). The combination of a linear change in mean WW genetic potential from MW change with a slightly nonlinear response in actual WW between MW scenarios (Appendix 3.2: Table 3.A2.1) implies nutritional limitations under Flint Hills grazing conditions in the absence of creep feed are likely impeding the ability to achieve pre-weaning calf growth genetic potential.

For the modeled scenarios, calves do not receive creep feed during the grazing season. Therefore, the increase in KPC SPA with increasing PL category highlights improved pre-weaning calf growth with additional nutrient intake. Aggregated across all MW, the smaller increase in median actual WW from 11.3 kg/d PL to 13.6 kg/d PL than the median actual WW increases between lower PL categories (Appendix 3.2: Table 3.A2.2) suggests a nonlinear KPC SPA response to increased PL when cow nutrient demands are met (Fig. 3.1).

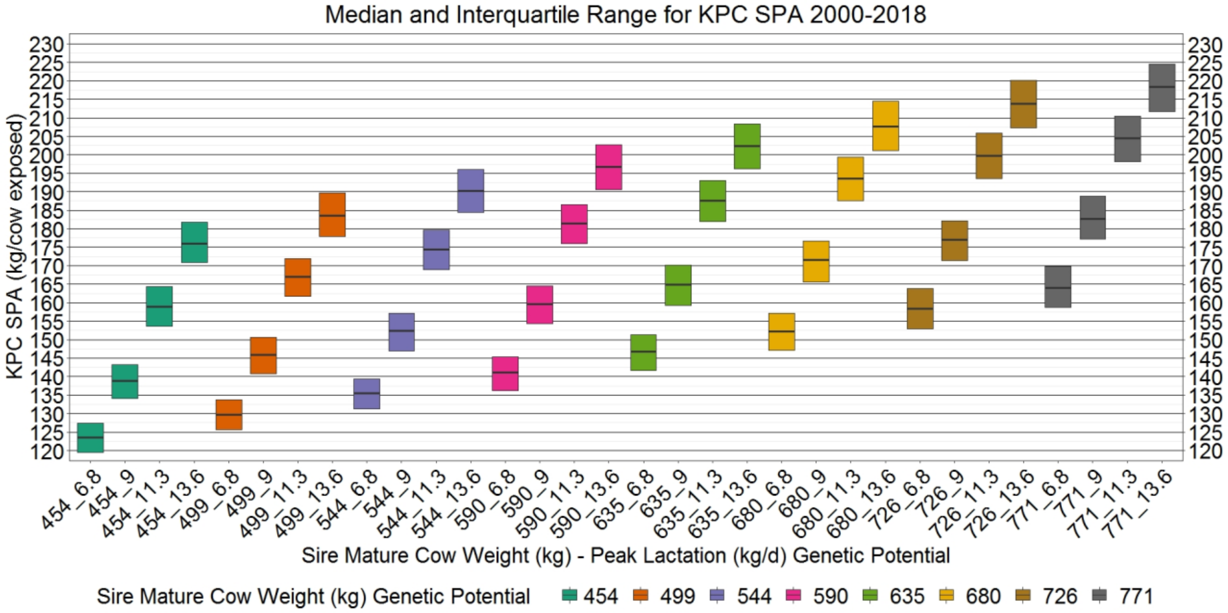

Figure 3.1 Boxplots representing the median, 25th percentile, and 75th percentile of KPC SPA aggregated across all iterations and production years 2000 through 2018 for each MW and PL category combination.

Despite a 22 kg increase in Steer WW genetic potential from calves born in 2000 to calves born in 2018, Adjusted Steer WW and actual WW, unadjusted for sex, showed no meaningful change from 2000 to 2018 (Appendix 3.2: Fig. 3.A2.7). Hence, because of the consistent reproductive rate previously discussed, KPC-SPA aggregated across all cow types varied little from 2000-2018 (Fig. 3.2). Utilizing WW data from a variety of industry sources, Lalman et al. (2019) reported a similar pattern in static WW over the same time frame.

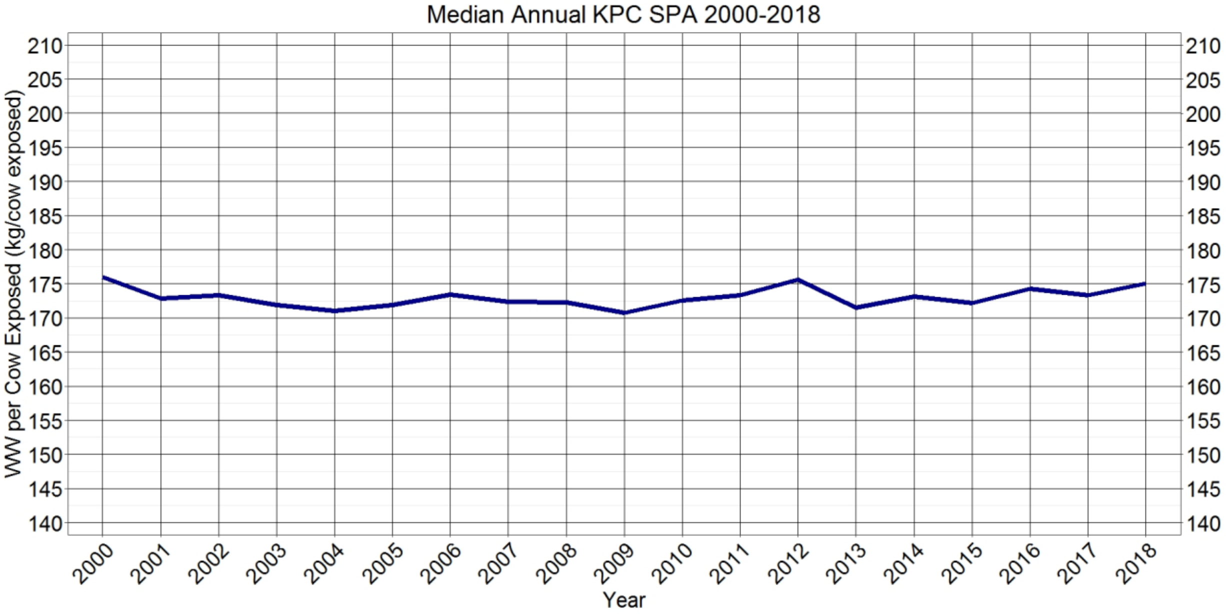

Figure 3.2. Median KPC SPA across all MW and PL category combinations for all iterations and production years 2000 through 2018.

Kilograms Weaned per Net Energy for Maintenance, Gestation, and Lactation Intake

Annual kg weaned per hundred NEm intake (KW NEmH) is calculated by dividing total kg of calf weaned by whole system NEm (Mcal) intake (breeding females, calves, and replacement heifers) for a given production year and multiplying by 100. Figure 3.2 summarizes KW NEmH across all iterations and all production years (i.e., over the long run) for each of the 32 simulated combinations of MW category and PL category. Under the simulated model scenarios, KW NEmH decreased with increased MW and increased with increased PL.

Scasta et al. (2015) reported that biological efficiency (kg forage DMI/Adj. WW) favored smaller cows across 5 weight classes within the same breed type and similar matings in a semi-arid environment. The comparable results between the limited resource environment in Scasta et al. (2015) and the ample resources provided in the present simulation suggest that even across varied environments the added WW associated with larger MW may not be enough to offset the added nutrient requirements of larger MW when considering energy intake relative to calf weight weaned. Such a statement assumes the absence of creep feeding and that milk production does not change with MW.

The magnitude of KW NEmH change was much greater across PL than MW. Applying a comparably designed individual based model, Tedeschi et al. (2006) also reported that biological efficiency (Mcal ME per kg weaned) improved with increased PL, and that PL impacts efficiency more than MW. Further supporting both the present and Tedeschi et al. (2006) simulation studies, a live animal study in which cows were managed in small groups to best meet nutrient requirements, Miller et al. (1999), reported biological efficiency improvement with increased milk for 2 of 3 cow types when regressing weaning gain (g) per Mcal metabolizable energy (ME) on milk yield (kg/d). In Miller et al. (1999), the absolute coefficient value of milk yield related to biological energy efficiency decreased as average cow type milk yield increased. Although Miller et al. (1999) failed to find a significant nonlinear relationship between biological energy efficiency and milk yield, the possibility is raised and seems to appear in the present study (Fig. 3.2; Appendix 3.2: Table

3.A2.4). Contradictory to the present study, Montano-Bermudez and Nielsen (1990) found biological efficiency (g weaned/Mcal ME) favored low milk cows over medium and high milk groups. Clutter and Nielsen (1987) used the same southeast Nebraska cow herd and describe identical management across cow types with cows wintered as a single group, suggesting the possibility that individual cow nutrient demands and availability may not have been matched as closely as Miller et al. (1999) and the present simulation design. Jenkins and Ferrell (1994) found the biological efficiency (g calf weaned/kg DM/cow exposed) ranking of nine beef breeds with different genetic potential for growth and milk varied greatly across different dry matter intake (DMI) levels, emphasizing that the interaction between production potential and nutrient availability may cause disparity in biological efficiency across different environments.

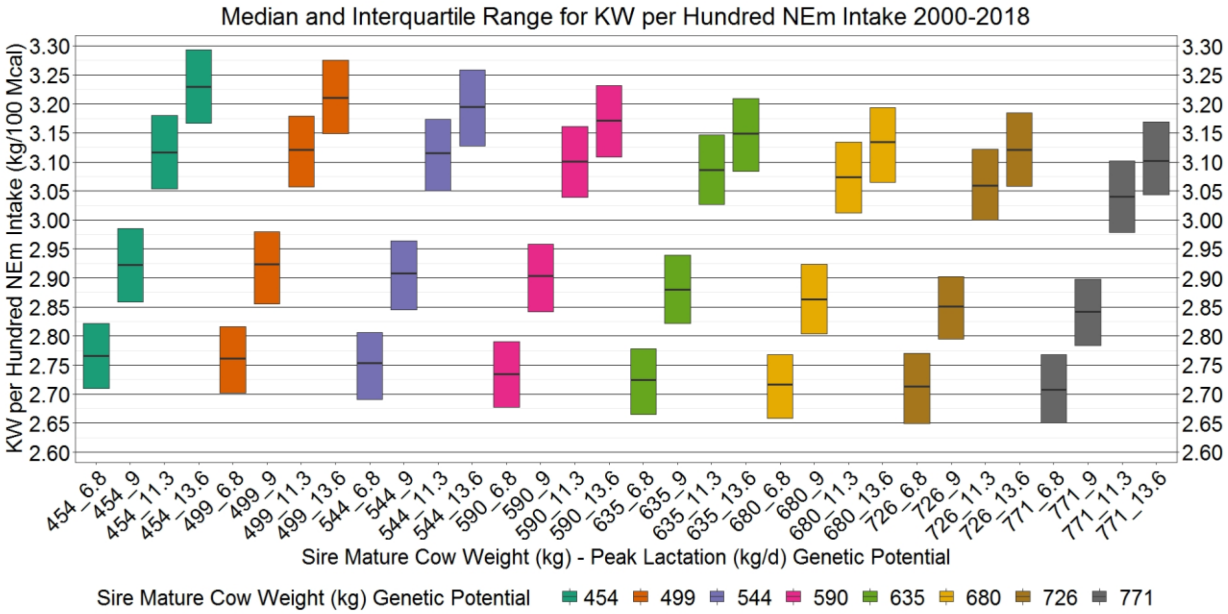

Figure 3.3. Boxplots representing the median, 25th percentile, and 75th percentile of KW NEmH aggregated across all iterations and production years 2000 through 2018 for each MW and PL category combination.

There was slight year-to-year re-ranking regarding median KW NEmH between adjacent MW categories (Fig. 3.4). Considering the complex interactions between endogenous model variables, the root re-ranking cause was not identified. Biological efficiency favored higher PL for each simulated year (Fig. 3.5).

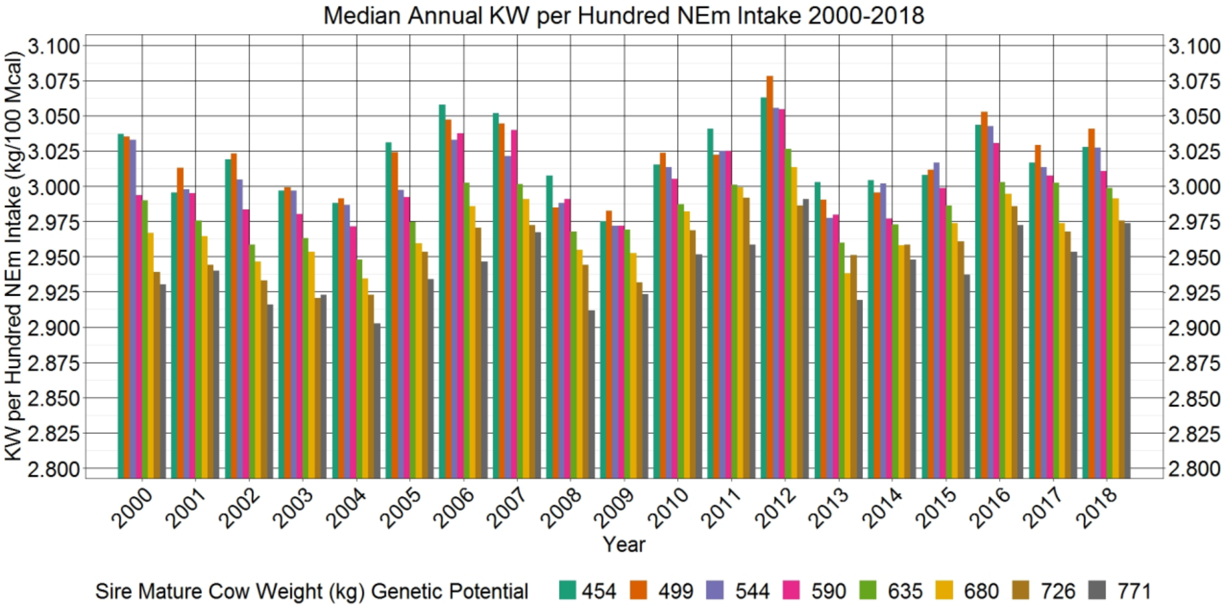

Figure 3.4. Median KW NEmH by MW category across all iterations for each production year from 2000 through 2018.

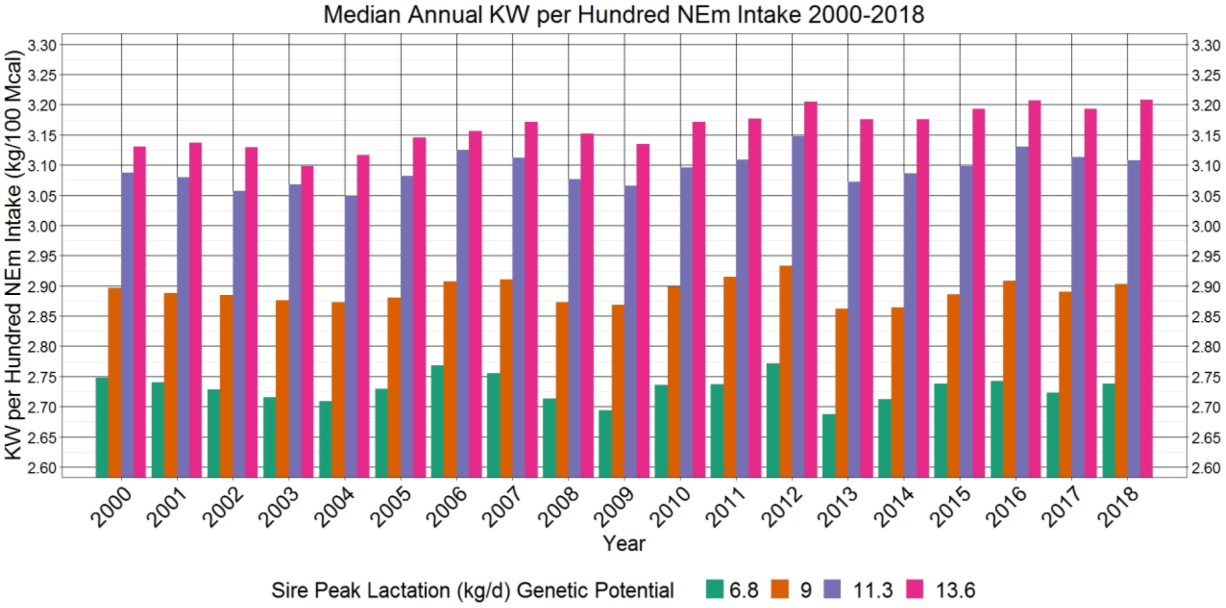

Figure 3.5. Median KW NEmH by PL category across all iterations for each production year from 2000 through 2018.

Economic Efficiency

Return per Breeding Female

Aggregating median annual return over fed ration, pasture, replacement, and interest expense per breeding female exposed across all iterations and all production years (i.e., over the long run) indicates nuanced interaction between MW and PL (Fig. 3.6). Pooling all PL classes within MW class, median annual return per breeding female decreased with increased MW, except between 454 kg and 499 kg MW categories (Appendix 3.2: Table 3.A2.5). The magnitude of change between adjacent MW categories was inconsistent (Appendix 3.2: Table 3.A2.5). Doye and Lalman (2011) and Stockton et al. (2016) also found that return per breeding female favored small cows when calves were sold at weaning. Pooling all MW classes within PL, median annual return per breeding female increased with increased PL (Appendix 3.2: Table 3.A2.6). The median annual return per breeding female difference between 9 kg/d PL and 11.3 kg/d PL was substantially greater than the difference between the other adjacent PL categories (Fig. 3.6, Appendix 3.2: Table 3.A2.6). In an abundant resource environment, Miller et al. (1999) defined gross margin as revenue minus feed cost and found that gross margin increased with milk production, supporting the present research. The interquartile range in annual return per breeding female increased with both increased MW class and increased PL class (Fig. 3.6, Appendix 3.2: Table 3.A2.5 and Table 3.A2.6).

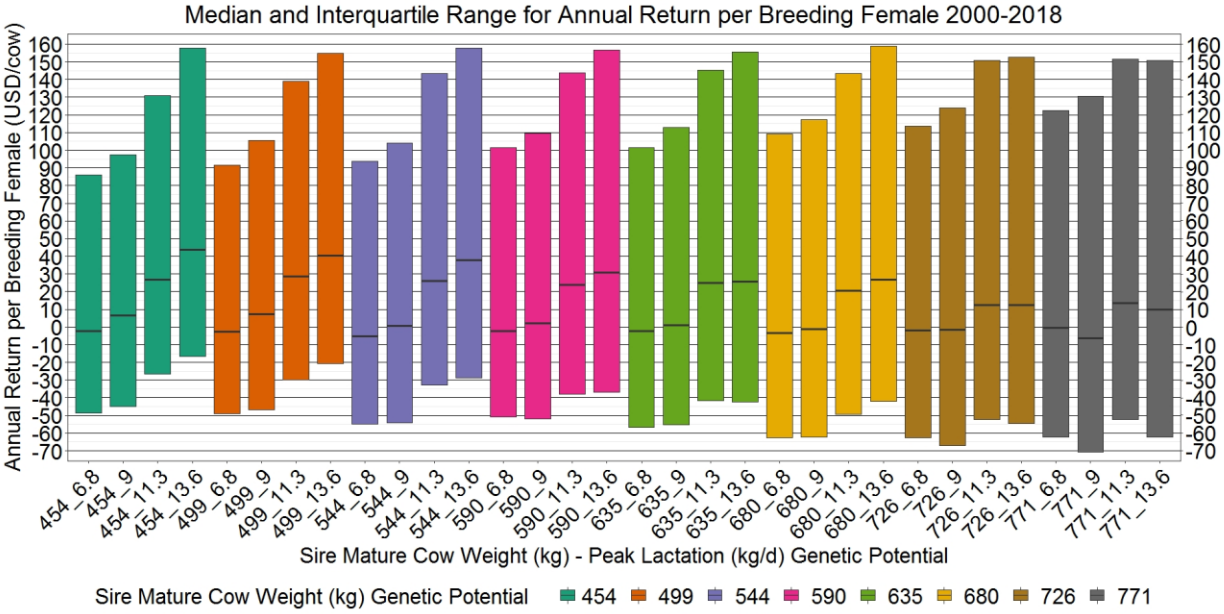

Figure 3.6. Boxplots representing the median, 25th percentile, and 75th percentile of annual return over fed ration, pasture, replacement, and interest expense per breeding female aggregated across all iterations and production years 2000 through 2018 for each MW and PL category combination.

Fig. 3.7 illustrates that median annual return per breeding female is highly variable across years and that the ranking between cow types depends greatly on yearly conditions. In the present simulation, because nutrient demands are generally met for all individual animals, regardless of cost per nutrition unit, environmental impact on returns is manifest in market prices. Therefore, year-to-year differences and cow type re-ranking in annual return per breeding female primarily result from the changing relationship between input and output prices. Fig. 3.8 demonstrates that as calf price increased relative to fed ration price, return per breeding female improved and larger cows benefited more than smaller cows. In years where calf price was particularly elevated relative to fed ration price (e.g. 2014 and 2015), return per breeding female increased with increased MW class. In years where calf price was noticeably lower relative to fed ration price (e.g. 2011 and 2012), return per breeding female favored smaller cows. Although the aggregated finding that return per breeding female increased with increased PL category held true in most specific years, there was slight re-ranking among adjacent PL categories when calf price was lower relative to fed ration price (e.g. 2011 and 2012) (Fig. 3.9).

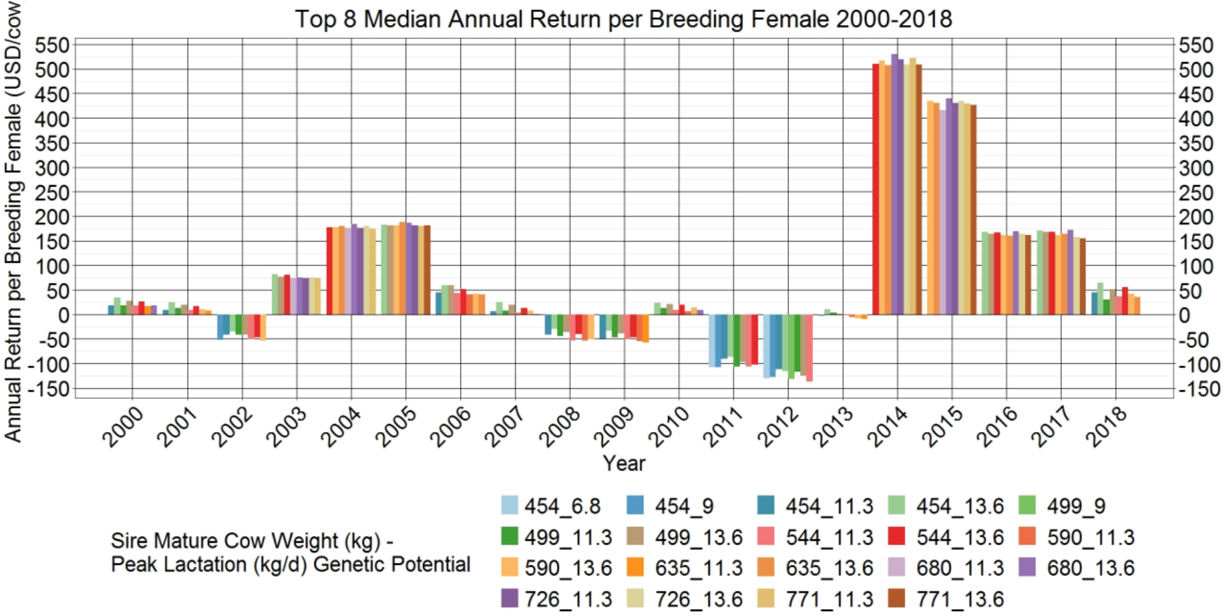

Figure 3.7. Columns represent the top eight (25%) MW and PL category combinations across all iterations ranked by median return over fed ration, pasture, replacement, and interest expense per breeding female for each production year from 2000 through 2018.

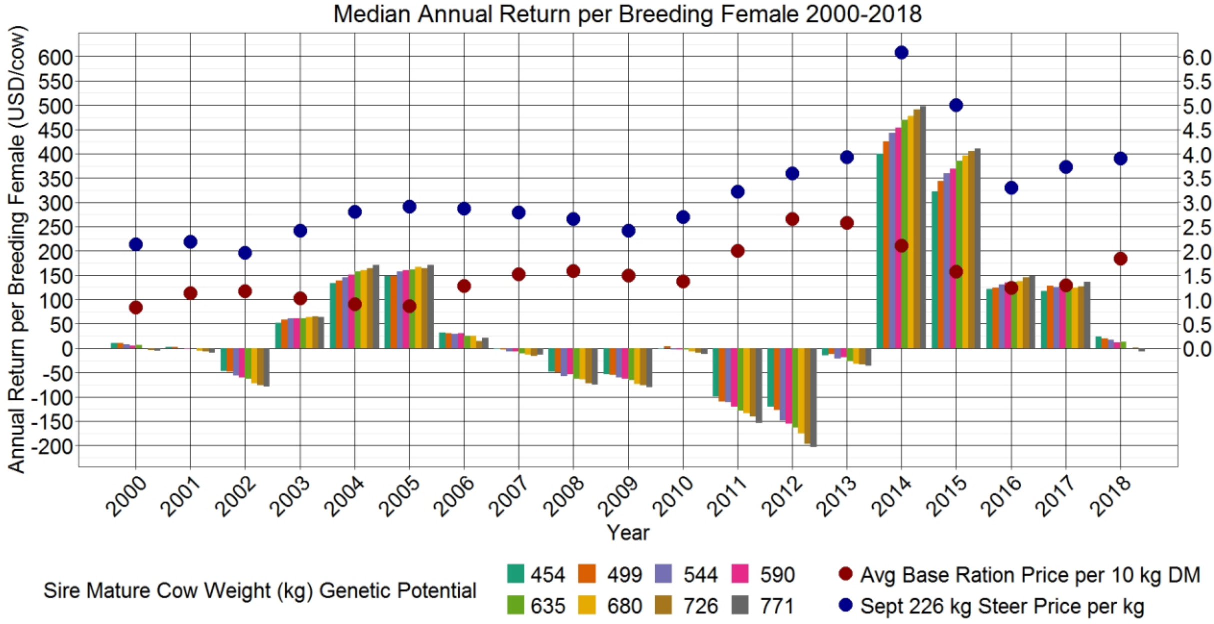

Figure 3.8. Columns represent the median return over fed ration, pasture, replacement, and interest expense per breeding female by MW category across all iterations for each production year from 2000 through 2018. Dots represent the average base ration price per 10 kg DM and the September price per kg for a 226 kg steer for each production year. Ration and cattle prices are exogenous variables based on historical data.

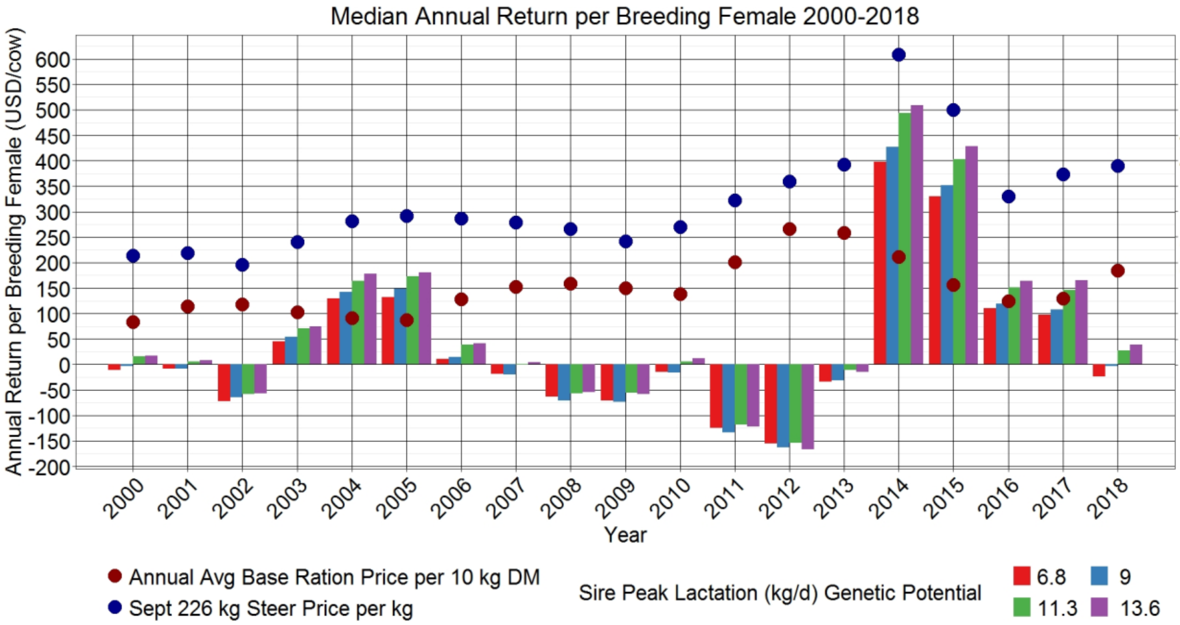

Figure 3.9. Columns represent the median return over fed ration, pasture, replacement, and interest expense per breeding female by PL category across all iterations for each production year from 2000 through 2018. Dots represent the average base ration price per 10 kg DM and the September price per kg for a 226 kg steer for each production year. Ration and cattle prices are exogenous variables based on historical data.

Return per Grazing Acre

All iterations and all production years combined (i.e., over the long run), annual return over fed ration, pasture, replacement, and interest expense per grazing acre tended to increase as MW category decreased. (Fig. 3.10; Appendix 3.2: Table 3.A2.7). Increased PL typically led to increased annual return per grazing acre (Fig. 3.10; Appendix 3.2: Table 3.A2.8); however, at upper MW classes the trend was less pronounced with PL ranking by annual return per grazing acre even reversed between a few adjacent PL classes (Fig. 3.10). Similar to the present study, Bir et al. (2018) reported increased NPV per acre with ever shrinking cow weight, while Doye and Lalman (2011) concluded that return to a fixed land base increased with more moderate vs larger cows.

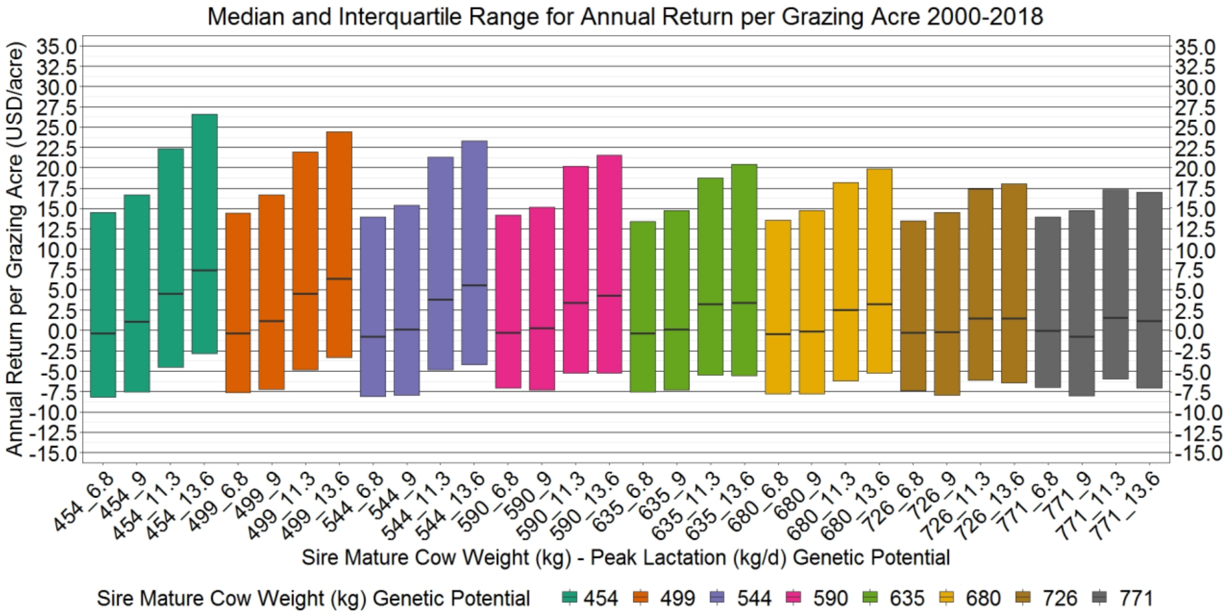

Figure 3.10. Boxplots representing the median, 25th percentile, and 75th percentile of annual return over fed ration, pasture, replacement, and interest expense per grazing acre aggregated across all iterations and production years 2000 through 2018 for each MW and PL category combination.

Figure 3.11 highlights the difference between return per cow and return per acre as economic efficiency metrics. Contrasting with return per breeding female, return per grazing acre increased consistently with decreased MW category in years with positive return, whereas difference in return per acre between MW categories was miniscule with no noticeable pattern in years with negative return. This results from the relationship between the ratios' numerator and denominator. More acres per cow with larger animals dilutes deviation from zero return per cow in the numerator across more acres in the denominator. The opposite is true with the fewer acres required for smaller cows: when compared to return per cow both positive and negative returns are magnified. Thus, the inconsistency between Fig. 3.8 and Fig. 3.11.

In the present simulation study, PL was not used to determine stocking rate. Therefore, Fig. 3.12 aligns well with Fig. 3.9 with a less reliable trend in PL ranking by return per grazing acre in years with negative return. The interquartile range of annual return per grazing acre decreased slightly with increased MW and increased slightly with increased PL (Appendix 3.2: Table 3.A2.5 and Table 3.A2.7).

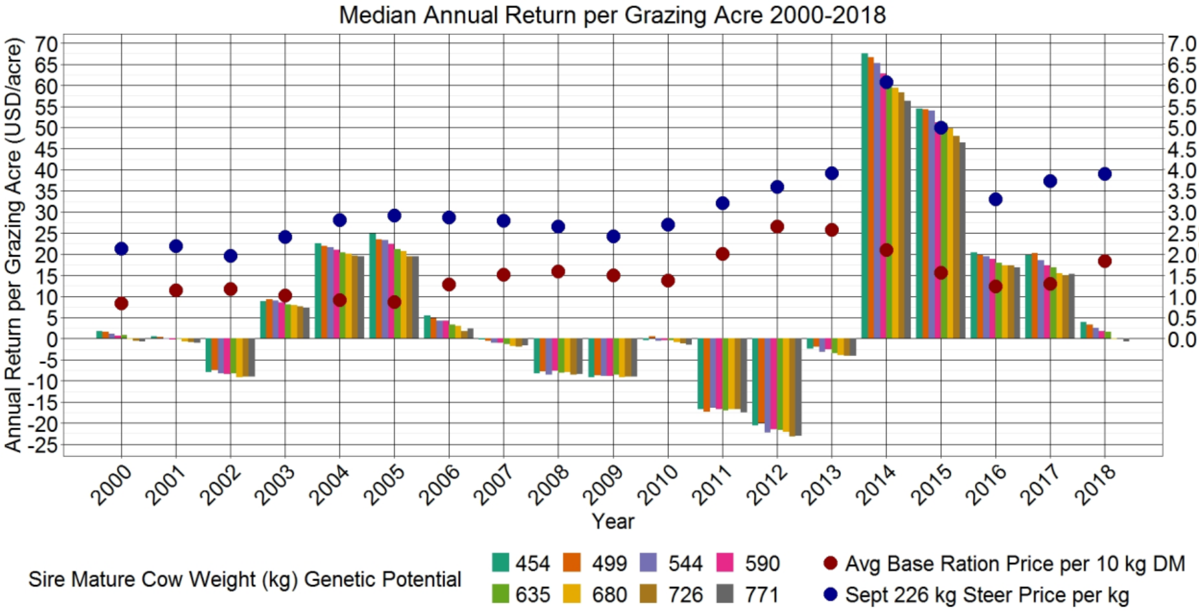

Figure 3.11. Columns represent the median return over fed ration, pasture, replacement, and interest expense per grazing acre by MW category across all iterations for each production year from 2000 through 2018. Dots represent the average base ration price per 10 kg DM and the September price per kg for a 226 kg steer for each production year. Ration and cattle prices are exogenous variables based on historical data.

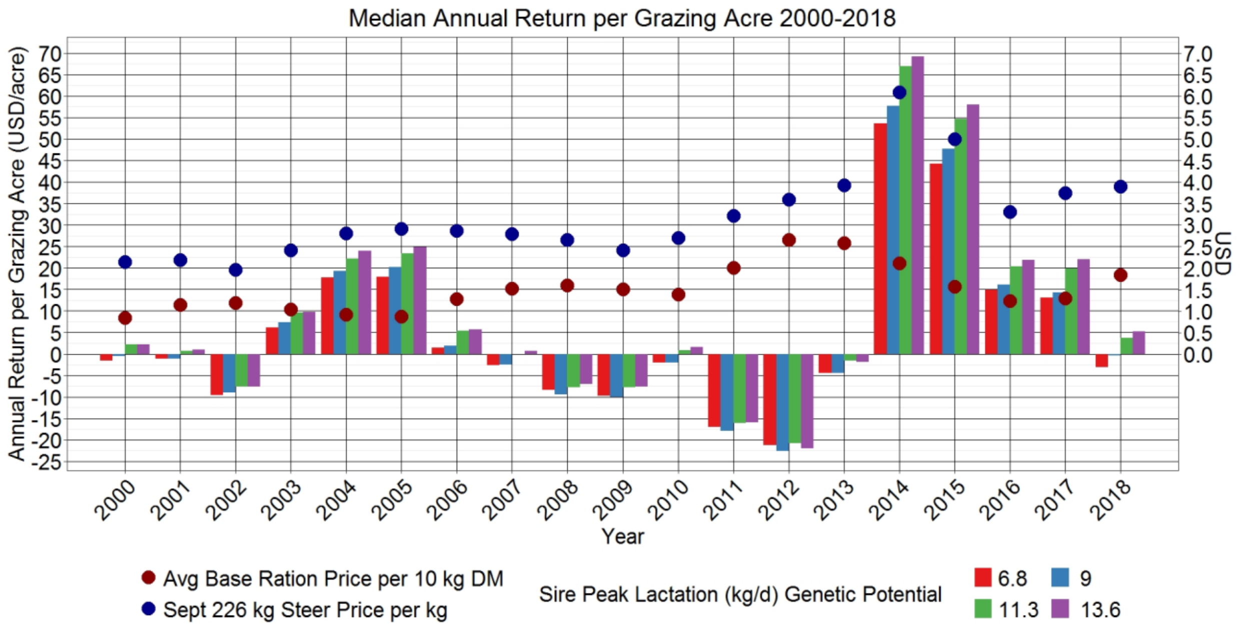

Figure 3.12. Columns represent the median return over fed ration, pasture, replacement, and interest expense per grazing acre by PL category across all iterations for each production year from 2000 through 2018. Dots represent the average base ration price per 10 kg DM and the September price per kg for a 226 kg steer for each production year. Ration and cattle prices are exogenous variables based on historical data.

Return on Investment

Whereas return per breeding female and return per acre denominate an economic value with biological variables; perhaps return on investment (ROI) is a truer measure of economic efficiency as output and input are characterized in like terms: dollar returned per dollar invested. Across all iterations and production years (i.e., over the long run) ROI (return on fed ration, pasture, replacement, and interest expense) tended to decrease with increased MW category (Fig. 3.13; Appendix 3.2: Table 3.A2.9), and increase with increased PL category (Fig. 3.13; Appendix 3.2: Table 3.A2.10). As noted in several other efficiency metrics, the effect of changing MW and PL on ROI seems to be nonlinear, particularly with increased MW category (Fig. 3.13; Appendix 3.2: Table 3.A2.9 and Table

3.A2.10). The ROI interquartile range decreased slightly with increased MW and increased slightly with increased PL (Appendix 3.2: Table 3.A2.9 and Table 3.A2.10).

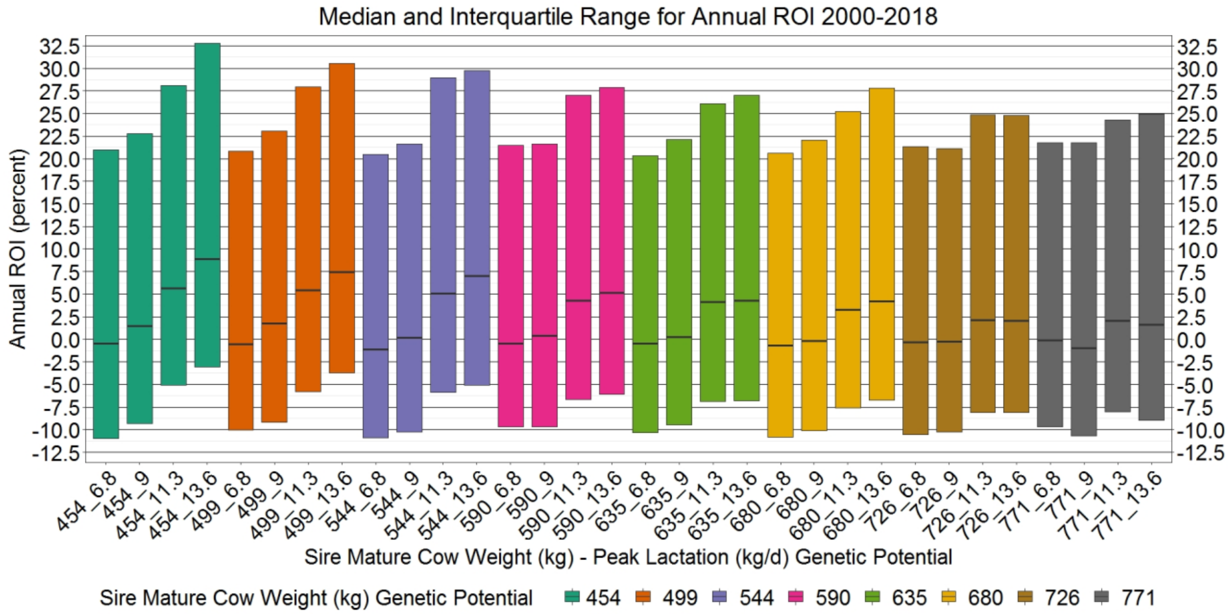

Figure 3.13. Boxplots representing the median, 25th percentile, and 75th percentile of annual ROI (return on fed ration, pasture, replacement, and interest expense) aggregated across all iterations and production years 2000 through 2018 for each MW and PL category combination.

From year to year, ROI generally favored smaller MW (Fig. 3.14), although slight re-ranking between adjacent MW categories was common. As expected, ROI was greater in years where calf price was higher relative to fed ration price (Fig. 3.14). Generally, ROI favored increased PL in all specific years (Fig. 3.15). The change with greatest magnitude and directional consistency was PL between 9 kg/d and 11.3 kg/d (Fig. 3.15; Appendix 3.2: Table 3.A2.9). ROI ranking between PL 11.3 kg/d and 13.6 kg/d was particularly inconsistent. In contrast to this study, van Oijen et al. (1993) found that ROI increased with decreased milk. As previously discussed, the cattle were managed as described in Clutter and Nielsen (1987), suggesting important differences from the present study. Not surprisingly given outcomes previously described, the yearly top 25% (8 of 32) MW-PL combinations for ROI favored smaller, heavier milking cows (Fig. 3.16).

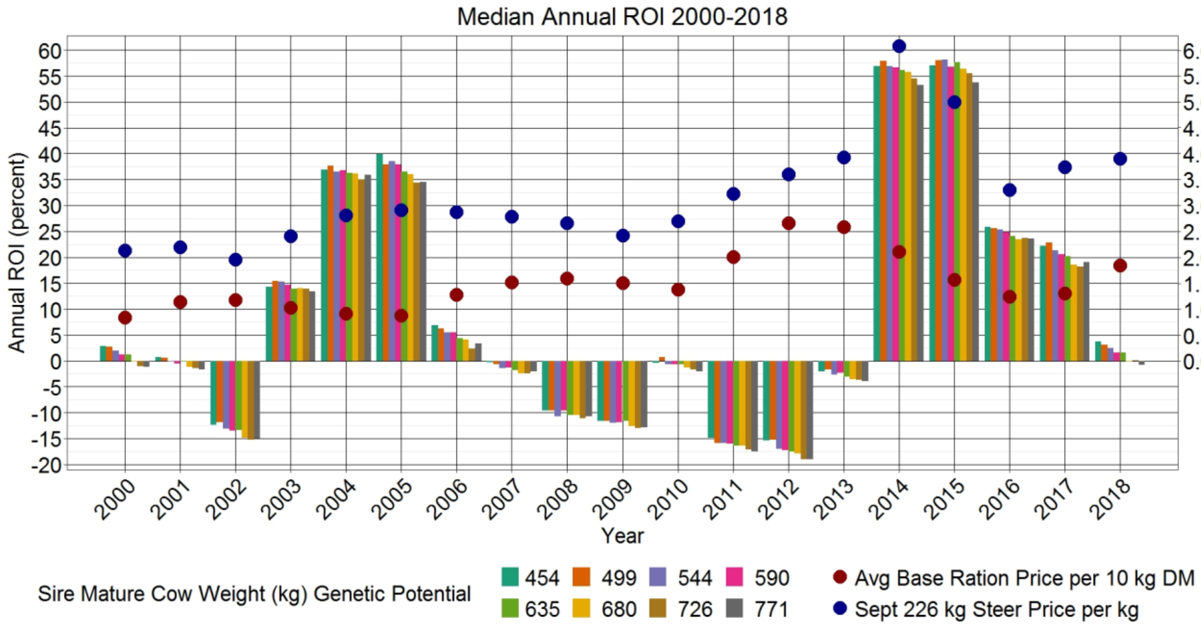

Figure 3.14. Columns represent the median annual ROI (return on fed ration, pasture, replacement, and interest expense) by MW category across all iterations for each production year from 2000 through 2018. Dots represent the average base ration price per 10 kg DM and the September price per kg for a 226 kg steer for each production year. Ration and cattle prices are exogenous variables based on historical data.

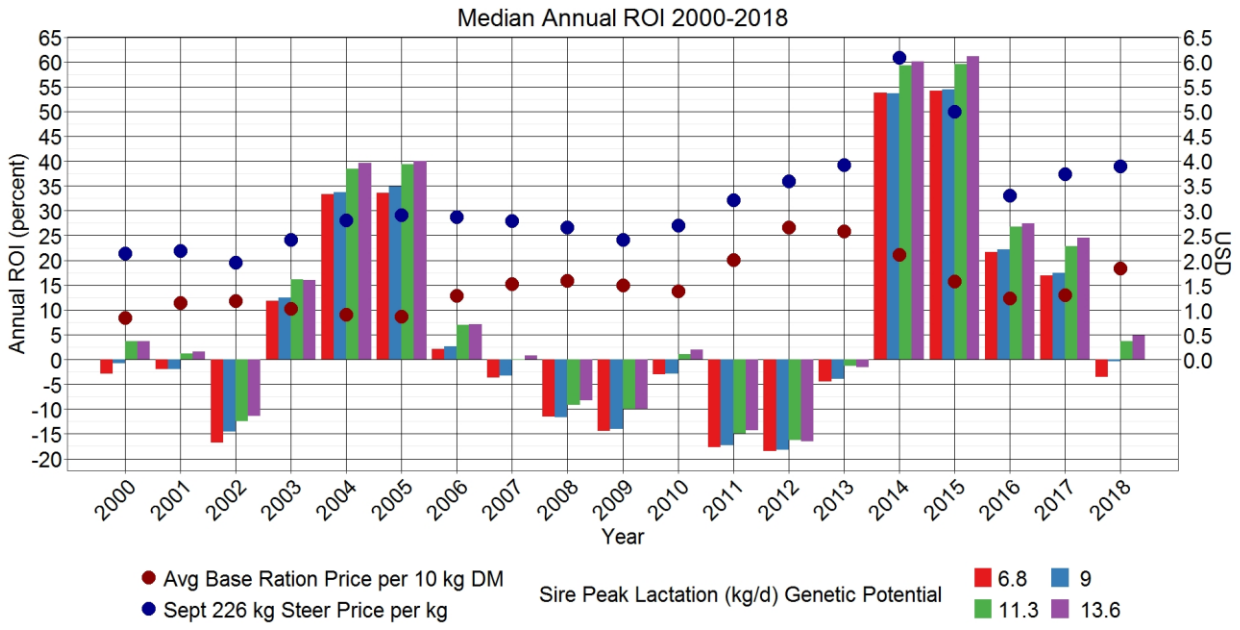

Figure 3.15. Columns represent the median annual ROI (return on fed ration, pasture, replacement, and interest expense) by PL category across all iterations for each production year from 2000 through 2018. Dots represent the average base ration price per 10 kg DM and the September price per kg for a 226 kg steer for each production year. Ration and cattle prices are exogenous variables based on historical data.

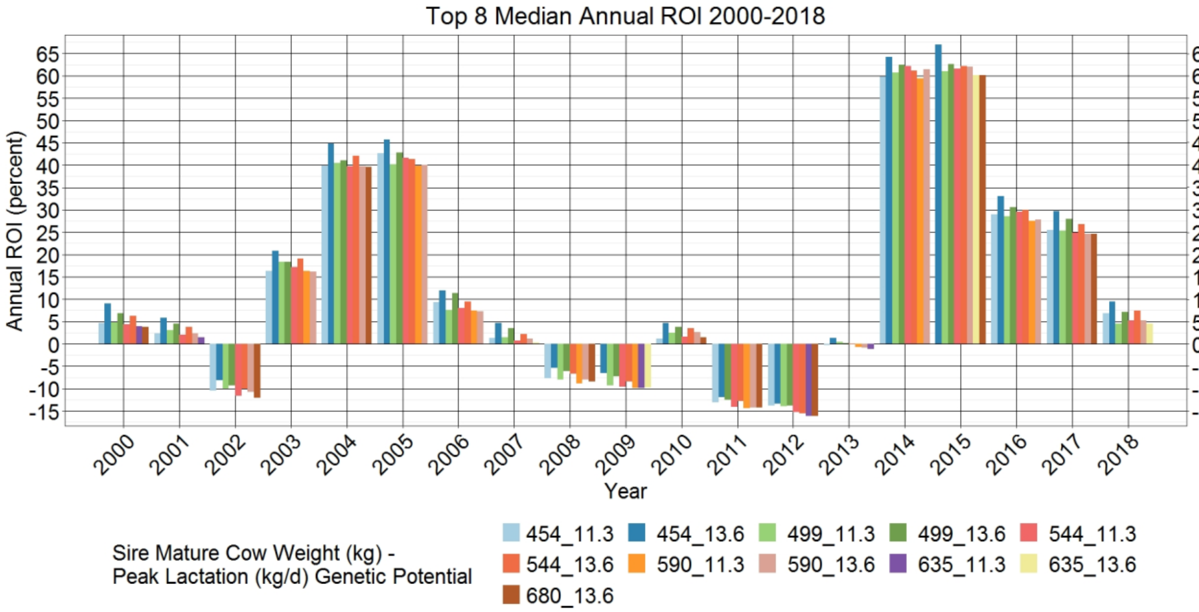

Figure 3.16. Columns represent the top eight (25%) MW and PL category combinations across all iterations ranked by median annual ROI (return on fed ration, pasture, replacement, and interest expense) for each production year from 2000 through 2018.

General

A useful simplification of a complex reality is the best a model can achieve. The present study was parameterized to match the biological and economic conditions of the Kansas Flint Hills from 2000 to 2018 for an Angus cow herd retaining replacement females and generally meeting the nutrient requirements of all breeding females, regardless of feed cost. Expenses more associated with enterprise type and scale (labor, fuel, utilities, etc.) were not considered. Focus was narrowed to expenses specific to cow type (fed ration, pasture, replacement; and interest on fed ration, pasture, and replacement expenses).

Extrapolation of model outcomes to other management scenarios and time frames should be exercised with caution. The same caution should be considered before generalizing the results of a physical study regarding a single cow-calf enterprise at a specific location and over a particular time frame. The stochastic nature of the present study highlights the biological variation inherent to beef cattle production, even under identical management, environment, and decision rules.

Model results emphasize the year-to-year variation in economic efficiency in both absolute terms and cow type ranking. Unfortunately, cattle's generation interval dictates that optimizing cow type on an annual basis is not feasible, even if future conditions were known with certainty. Thus, a producer should determine which cow type best fits their environment and marketing strategy over the long run.

The present scenario makes two key assumptions:

1) All simulated cow types exist in reality.

2) There is no calf price differentiation based on projected performance after weaning.

Table 3.1 shows median ROI and rank for the top 25% (8 of 32) of all modeled cow types across all simulation iterations and all production years (i.e., over the long run). In the full ranking list, there were several cow types with a negative median annual ROI (Appendix 3.2: Table 3.A2.11). All cow types with 11.3 kg/d or 13.6 kg/d PL had a positive median annual ROI over the full simulation (Appendix 3.2: Table 3.A2.11).

Table 3.1. The top eight (25%) MW and PL category combinations aggregated across all iterations and production years 2000 through 2018 ranked by median annual ROI (return on fed ration, pasture, replacement, and interest expense) assuming all simulated MW and PL combinations exist and no price differentiation between calves from different MW breeding systems.

Sire Mature Cow Weight (kg) Genetic Potential	Sire Peak Lactation (kg/d) Genetic Potential	Median Annual ROI (percent) (USD/USD)	Rank
454	13.6	8.9	1
499	13.6	7.4	2
544	13.6	7.0	3
454	11.3	5.6	4
499	11.3	5.4	5
590	13.6	5.1	6
544	11.3	5.1	7
635	13.6	4.3	8

Exploring measured cow weight, stated biological type, and lactation curves in the beef cattle lactation literature suggests that 454 kg MW-13.6 kg/d PL and 499 kg MW-13.6 kg/d PL cows may not exist in the current beef cow population (Casebolt, 1984; Clutter and Nielsen, 1987; Jenkins and Ferrell, 1984; Marston et al., 1992; Miller et al., 1999; Minick et al., 2001). Cows categorized as 544 kg MW-13.6 kg/d PL may also be scarce.

The price paid for calves and feeder cattle is largely determined by projected growth and carcass characteristics. Over the years, numerous studies have shown that prices differ for cattle with different frame scores (McCabe et al., 2019; Schroeder et al., 1988; Schulz et al., 2010). Schulz et al. (2010) estimated that feeder cattle in the small framed category were discounted \$0.13/kg from a medium frame base. It is feasible that calves from a mating system with a 454 kg sire MW genetic potential would be classified as small frame. At the very least, a cattle feeder that paid average price for such calves would likely be disappointed in their performance and discount them in subsequent years. A simple breakeven calculation under current market conditions assuming steer calves from the 454 kg sire MW genetic potential herd finish 90 kg lighter and gain 0.23 kg/d less than the average fed steer generates a \$0.11/kg to \$0.22/kg discount in calf price, depending on in-weight and projected fed price, similar to Schulz et al. (2010). Applying a \$0.13/kg discount to the median actual WW of both steer and heifer calves in the 454 kg sire MW categories; and then decreasing both weaned calf value and replacement expense accordingly yields a net effect on median return per breeding female of -16.06, -18.03, -20.76, and -22.96 USD/cow for the respective 6.8 to 13.6 kg/d PL categories.

Assuming 454 kg MW-13.6 kg/d PL and 499 kg MW-13.6 kg/d PL cows do not exist, and applying the described discount to the remaining 454 kg MW categories generates the top eight long-run (2000 through 2018) cow type ranking displayed in Table 3.2. There was 0.9 percentage point drop in ROI between the 8th and 9th ranked cow type in the expanded version of Table 3.2 (Appendix 3.2: Table 3.A2.12).

Table 3.2. The top eight MW and PL category combinations aggregated across all iterations and production years 2000 through 2018 ranked by median annual ROI (return on fed ration, pasture, replacement, and interest expense) assuming 454 kg MW-13.6 kg/d PL and 499 kg MW-13.6 kg/d PL cows do not exist, and applying a $0.13/kg discount to the remaining 454 kg MW categories.

Sire Mature Cow Weight (kg) Genetic Potential	Sire Peak Lactation (kg/d) Genetic Potential	Median Annual ROI (percent) (USD/USD)	Rank
544	13.6	7.0	1
499	11.3	5.4	2
590	13.6	5.1	3
544	11.3	5.1	4
635	13.6	4.3	5
590	11.3	4.3	6
680	13.6	4.2	7
635	11.3	4.1	8

Over the past several decades multiple studies using various profitability and economic efficiency metrics have pointed to smaller mature weight and/or lighter milking cows as the path to increase profitability (Bir et al., 2018; Doye and Lalman, 2011; Scasta et al., 2015; Stockton et al., 2016; van Oijen et al. 1993). Others have found increased profitability with larger and/or heavier milking cows (Armstrong et al., 1990; Miller et al., 1999). The present research suggests several reasons for contrasting conclusions including differences in economic and resource conditions at different points in time and geography, as well as differences in economic efficiency metrics.

Assuming all modeled combinations of MW and PL exist in the U.S. beef cow population and no calf price differentiation across cow types, under the described scenario-specific parameters, long-run median ROI is maximized with the lightest weight, heaviest milking cows (Table 3.1). If the possible non-existence of 454 kg MW-13.6 kg/d PL and 499 kg MW-13.6 kg/d PL cows is considered and the market discounts calves from the 454 kg

MW category, long-run ROI ranking favors moderate weight, above average milking cows (Table 3.2).

In a recent CattleFax survey (CattleFax, 2018), 60 percent of respondents who planned to expand their cow herd intended to do so by retaining raised heifers. Forty-four percent of respondents sold calves at or shortly after weaning (CattleFax, 2018). Ishmael (2020) communicated recent survey results where 53% of respondents reported a predominantly Angus cow herd and 55% most recently purchased an Angus bull. A seemingly large portion of the cow-calf sector operates under the genetic, replacement, and marketing strategies simulated. Beef industry consultants and extension specialists have long encouraged producers to establish a uniform cow herd that can maintain a BCS 4 to 6 (1-9 scale) under a specific operation's environment and management resources in order to reach pregnancy percentages above 90 percent. Under the simulated scenario where cows produced in such conditions, and across all iterations and production years, the median BCS 5 MW and the median PL of the top eight ROI cow types in Table 3.2 was 587 kg (1294 pounds) and 12.45 kg/d (27.45 pounds/d), respectively. McMurry (2009) estimated the average U.S. cow at 612.25 kg (1350 pounds), while the CHAPS database reported a 629.9 kg (1389 pound) benchmark cow weight for 2018 (CHAPS, 2018). Perhaps for the majority of U.S. cow-calf producers that operate in non-arid climates and follow recommended management practices, the past two decades have dictated that the most economically efficient (ROI) cow weighs between 544 kg (1200 pounds) and 635 kg (1400 pounds) and has a peak lactation near 11.3 kg/d (25 pounds/d).

By accounting for the complex interactions, dynamic conditions, and feedback structure of beef cattle production, the modeling technique applied in the present study opens the door for further investigation into the biology and economics of a multitude of beef cattle production scenarios.

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Appendix 3.1: Model Parameters

Table 3.A1.1. Initialization parameters.

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
Iterations	Deterministic	100	User-defined	The number of iterations the user wishes to run an *i* production year simulation
Initial breeding herd size at calving	Deterministic	100	User-defined	
Breeding herd size goal	Deterministic	100	User-defined	The breeding herd size the user wishes to achieve.
Years to herd size	Deterministic	1	User-defined	The number of years the user wishes to pass in achieving the breeding herd size goal.
Initial heifer replacement rate	Deterministic	0.125	User-defined (default from Wittum et al.(1994), USDA (2010), Cushman et al. (2013), Ringwall (2014), and expert opinion)	
Breeding season start	Deterministic	May 1st	User-defined	
Breeding season end	Deterministic	July 3	User-defined	

Table 3.A1.2. Four-year rolling average Angus genetic trend for birth weight and weaning weight from 1992 to 2018.

Year	Angus Birth Weight EBV: Four Year Rolling Average	Angus Weaning Weight EBV: Four Year Rolling Average
1992	3.65	24.0
1993	3.80	27.0
1994	3.85	30.0
1995	3.80	32.5
1996	3.75	35.5
1997	3.75	38.0
1998	3.75	41.0
1999	3.80	44.5
2000	3.80	47.5
2001	3.80	51.0
2002	3.80	54.0
2003	3.80	57.0
2004	3.75	60.0
2005	3.7	62.5
2006	3.65	65.5
2007	3.55	68.5
2008	3.50	72.0
2009	3.40	75.5
2010	3.30	79.0
2011	3.20	82.0
2012	3.10	85.0
2013	3.00	88.0
2014	2.90	91.0
2015	2.85	94.5
2016	2.75	98.0
2017	2.70	102.0
2018	2.60	106.0

Adapted from AAA (2019a)

Table 3.A1.3. Genetic correlations.

Traits	Genetic Correlation	Reference
Weaning Weight: Mature Cow Weight	0.44	AAA (2019b)
Birth Weight: Weaning Weight	0.29	AAA (2019b)
Gestation: Birth Weight	0.30	Gregory et al. (1995)
Milk Production: Mature Cow Weight	0.14	Morris and Wilton (1976)

Table 3.A1.4. Price multipliers.

Price Multiplier Parameter	Distribution Type	Distribution Parameters	Reference	Notes
Fed Ration Expense	Normal	(1, 0.05)	Expert Opinion	
Pasture Lease Expense	Normal	(1, 0.05)	Expert Opinion	
Weaned Calf Price	Normal	(1, 0.01)	Expert Opinion	
Cull Cow Price	Normal	(1, 0.01)	Expert Opinion	

Table 3.A1.5. Manhattan, KS January through August Cumulative Precipitation.

Year	**Jan- Aug Cumulative Precipitation (in)**
1995	34.83
1996	23.61
1997	20.17
1998	24.15
1999	30.50
2000	15.43
2001	30.82
2002	18.43
2003	25.56
2004	32.54
2005	26.45
2006	26.2
2007	34.62
2008	33.07
2009	29.46
2010	26.70
2011	21.33
2012	17.46
2013	22.60
2014	23.88
2015	30.81
2016	31.01
2017	25.31
2018	19.98

From HPRCC (2019)

Table 3.A1.6. Grazing acre allocation for the eight scenario possibilities for sire mature cow weight genetic potential.

Sire Mature Cow Weight (kg) Genetic Potential	Full season grazing acres allocated per pair	Full season grazing acres allocated per yearling heifer	Grazing acres allocated per post-weaning replacement heifer
454	5.83	3.33	2.16
499	6.26	3.43	2.32
544	6.68	3.66	2.47
590	7.10	3.89	2.63
635	7.50	4.11	2.77
680	7.90	4.33	2.93
726	8.30	4.55	3.07
771	8.68	4.76	3.21

Table 3.A1.7. Model parameters for grazing expense (USD/per acre).

Year	Cow-Calf Pair: Full Summer Grazing Season	Post-Weaning Replacement Heifers: Partial Grazing Season	Yearling Heifers: Full Summer Grazing Season
2000	14.51	19.99	17.36
2001	14.27	19.62	17.04
2002	14.69	19.44	16.88
2003	14.80	19.66	17.07
2004	14.88	19.88	17.26
2005	16.35	20.18	18.49
2006	16.35	20.47	18.49
2007	17.17	21.94	18.49
2008	18.12	22.64	19.02
2009	17.85	22.93	17.70
2010	17.85	22.42	17.70
2011	20.71	25.73	23.51
2012	20.71	25.73	23.51
2013	20.71	26.83	23.51
2014	20.44	29.40	23.51
2015	20.17	31.24	26.42
2016	22.48	29.40	26.42
2017	24.25	26.46	24.04
2018	25.89	27.20	24.57

Table 3.A1.8. Ration nutrient densities by month.

Ration	**Month**	**NEm (Mcal/kg)**	**NEg (Mcal/kg)**	**DE (Mcal/kg)** (used for determining calf DMI)
Base (73% alfalfa, 19% wheat straw, and 8% corn)	Jan-Dec	1.2	0.64	NA
Supplement (60% alfalfa, 40% corn)	Jan-Dec	1.63	1.02	3.08
Bluestem Forage				
	Jan-Mar	0.71	0.18	1.89
	Apr-Jun	1.48	0.90	2.86
	Jul-Aug	1.10	0.54	2.12
	Sep-Dec	0.71	0.18	1.89

Calculated using estimates from NRC (2016) and Kuhl et al. (1993).

Table 3.A1.9. Assorted nutrition parameters.

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
Percent of forage remaining at end of grazing season- goal	Deterministic	40%		
Metabolizable energy (Mcal) per kg of diet	Deterministic	2.0	NRC 2016	Assumed to be the same for all diets. Only a factor when calculating NEm requirements from gestation.

Table 3.A1.10. Daily maximum DMI as percent of SBW by MW category and animal production category.

Animal Category	Maximum Daily DMI (percent of SBW)
454 kg MW	
Post-weaning Non-pregnant Replacement Heifer	2.9
Bred Yearling Heifer	2.9
Two-Year-Old Cow	2.5
Three-Year-Old Cow	2.5
Mature Cow (>= 4-Years-Old)	2.4
499 kg MW	
Post-weaning Non-pregnant Replacement Heifer	2.9
Bred Yearling Heifer	2.7
Two-Year-Old Cow	2.4
Three-Year-Old Cow	2.4
Mature Cow (>= 4-Years-Old)	2.3
544 kg MW	
Post-weaning Non-pregnant Replacement Heifer	2.9
Bred Yearling Heifer	2.7
Two-Year-Old Cow	2.4
Three-Year-Old Cow	2.4
Mature Cow (>= 4-Years-Old)	2.3

Table 3.A1.11 (*cont.*). Daily maximum DMI as percent of SBW by MW category and animal production category.

Animal Category	Maximum Daily DMI (percent of SBW)
590 kg MW	
Post-weaning Non-pregnant Replacement Heifer	2.7
Bred Yearling Heifer	2.7
Two-Year-Old Cow	2.3
Three-Year-Old Cow	2.3
Mature Cow (>= 4-Years-Old)	2.2
635 kg MW	
Post-weaning Non-pregnant Replacement Heifer	2.7
Bred Yearling Heifer	2.7
Two-Year-Old Cow	2.3
Three-Year-Old Cow	2.3
Mature Cow (>= 4-Years-Old)	2.2
680 kg MW	
Post-weaning Non-pregnant Replacement Heifer	2.7
Bred Yearling Heifer	2.7
Two-Year-Old Cow	2.3
Three-Year-Old Cow	2.3
Mature Cow (>= 4-Years-Old)	2.2

Table 3.A1.12 (*cont.*). Daily maximum DMI as percent of SBW by MW category and animal production category.

Animal Category	Maximum Daily DMI (percent of SBW)
726 kg MW	
Post-weaning Non-pregnant Replacement Heifer	2.7
Bred Yearling Heifer	2.7
Two-Year-Old Cow	2.2
Three-Year-Old Cow	2.2
Mature Cow (>= 4-Years-Old)	2.1
771 kg MW	
Post-weaning Non-pregnant Replacement Heifer	2.7
Bred Yearling Heifer	2.7
Two-Year-Old Cow	2.2
Three-Year-Old Cow	2.2
Mature Cow (>= 4-Years-Old)	2.1

Table 3.A1.13. BCS and corresponding body fat composition, percent of MSBW, and Mcal per kilogram of EBW loss and EBW gain.

BCS	Percent Body Fat EBW Composition	Percent of MSBW (BCS 5)	Mcal per kg EBW Loss	Mcal per kg EBW Gain
1	3.77	71.6	3.69	4.22
2	7.54	78.7	4.22	4.76
3	11.30	85.8	4.76	5.30
4	15.07	92.9	5.30	5.84
5	18.89	100.0	5.84	6.38
6	22.61	107.1	6.38	6.91
7	26.38	114.2	6.91	7.45
8	30.15	121.3	7.45	7.99
9	33.91	128.4	7.99	8.60

Adapted from NRC (2016)

Table 3.A1.14. Maximum base fed ration intake by animal production category.

Animal Production Category	**Maximum Base Fed Ration Intake (kg/d)**
Nursing Calf*	7.0
Post-weaning Non-pregnant Replacement Heifer	13.0
Bred Yearling Heifer	13.0
Two-Year-Old Cow	16.0
Three-Year-Old Cow	16.0
Mature Cow (>= 4-Years-Old)	16.0

*Base Fed Ration for Nursing Calves is equivalent to Supplement Ration for all other animal categories

Table 3.A1.15. Reproductive cyclicity.

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
Postpartum Interval (d)-Primiparous Cows			Ciccioli et al. (2003), Berardinelli et al. (2005), Endecott et al. (2007), and expert opinion	
BCS 1	Pert	(350, 350, 350)		
BCS 2	Pert	(135, 150, 165)		
BCS 3	Pert	(85, 100, 115)		
BCS 4	Pert	(65, 80, 95)		
BCS 5	Pert	(55, 70, 85)		
BCS 6	Pert	(45, 60, 75)		
BCS 7	Pert	(30, 45, 60)		
BCS 8	Pert	(30, 45, 60)		
BCS 9	Pert	(30, 45, 60)		

Table 3.A1.16 (*cont.*). Reproductive cyclicity.

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
PostPartum Interval (d)- Multiparous Cows			Graham (1982),Rutter and Randel (1984), Houghton et al. (1990), Cushman et al. (2007), Lents et al. (2008), and expert opinion	
BCS 1	Pert	(350, 350, 350)		
BCS 2	Pert	(135, 150, 165)		
BCS 3	Pert	(75, 90, 105)		
BCS 4	Pert	(55, 70, 85)		
BCS 5	Pert	(45, 60, 75)		
BCS 6	Pert	(35, 50, 65)		
BCS 7	Pert	(30, 35, 50)		
BCS 8	Pert	(30, 35, 50)		
BCS 9	Pert	(30, 35, 50)		
Dystocia Probability per Parturition			McDermott et al. (1990), USDA (2008), and expert opinion	
Multiparous Cow	Normal	(0.05, 0.01, lower=0)		
Primiparous Cow- Calf birthweight < 40.82 kg	Normal	(0.08, 0.01, lower=0)		
Primiparous Cow- Calf birthweight >= 40.82 kg	Normal	(0.5, 0.01, lower=0)		

Table 3.A1.17 (*cont.*). Reproductive cyclicity.

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
Additional PPI (d) resulting from dystocia	Normal	(10, 2, lower=0)	Doornbos et al. (1984), Bellows et al. (1988), and expert opinion.	
Pregnancy probability at d equal to estrous cycle length after breeding			Spell et al. (2001), Chagas et al. (2002), Aherin et al. (2018), and expert opinion	
Heifers	Normal	(0.71, 0.01, upper = 0.8)	Cundiff et al. (1974)	
Primiparous Cows	Normal	(0.61, 0.01, upper=0.8)	Cundiff et al. (1974)	
Multiparous Cows	Normal	(0.71, 0.01, upper = 0.8)	Cundiff et al. (1974)	

Table 3.A1.18 (*cont.*). Reproductive cyclicity.

Model Parameter	**Distribution Type**	**Distribution Parameters**	**Reference**	**Notes**
Pregnancy Loss				
Daily mean probability of returning to cyclicity after establishing pregnancy				
d 25 to d 45	Normal	(0.002, 0.0002, lower = 0)	Whittier et al. (1991), Lamb et al. (2008), Aherin et al. (2018), and expert opinion.	
d 46 to d 65	Normal	(0.0005, 0.00002, lower = 0)	Whittier et al. (1991), Lamb et al. (2008), Aherin et al. (2018), and expert opinion.	
d > 65	Normal	(0.0001, 0.00002, lower = 0)	Dziuk and Bellows (1983), van Wagtendonk-de Leeuw et al. (2000), Aherin et al. (2018), and expert opinion	
Gestation length	Normal	(285, 7)	Expert opinion	The length of each individual gestation is randomly determined by drawing from a normal distribution.

Table 3.A1.19. Culling.

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
Pregnancy determination (days after breeding season end)	Deterministic	60	User-defined	
Age (d) of oldest calf at weaning	Deterministic	220	User-defined	
Maximum cow age	Deterministic	13	User-defined	
Minimum culling percentage by cow age (years) (involuntary and voluntary combined)			Wittum et al.(1994), USDA (2010), Cushman et al. (2013), Ringwall (2014), and expert opinion	culls within age/exposed within age
1	Deterministic	5%		
2	Deterministic	10%		
3	Deterministic	6%		
4	Deterministic	6%		
5	Deterministic	6%		
6	Deterministic	6%		
7	Deterministic	6%		
8	Deterministic	6%		
9	Deterministic	8%		
10	Deterministic	10%		
11	Deterministic	40%		
12	Deterministic	50%		
13	Deterministic	100%		

Table 3.A1.20. Morbidity and mortality.

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
Daily probability of preweaned calf morbidity			Wittum et al. (1994), Sanderson and Dargatz (2000), USDA (2010), and expert opinion	
Dystocia and neonatal period (d 1-3 after parturition)	Normal	(0.01, 0.005, lower=0)		
No dystocia and neonatal period (d 1-3 after parturition)	Normal	(0.005, 0.001, lower=0)		
Dystocia and post-neonatal period to weaning	Normal	(0.0004, 0.00001, lower=0)		
No dystocia and post-neonatal period to weaning	Normal	(0.0002, 0.00001, lower=0)		

Table 3.A1.21 (*cont.*). Morbidity and mortality.

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
Daily probability of preweaned calf mortality			Laster and Gregory (1973), Patterson et al. (1987), Wittum et al. (1994), USDA (2010), and expert opinion	
Dystocia, no morbidity, and neonatal period	Normal	(0.06, 0.005, lower=0)		
Dystocia, morbidity, and neonatal period	Normal	(0.1, 0.0005, lower=0)		
No dystocia, no morbidity, and neonatal period	Normal	(0.01, 0.001, lower=0)		
No dystocia, morbidity, and neonatal period	Normal	(0.05, 0.001, lower=0)		
Dystocia, no morbidity, and post-neonatal period to weaning	Normal	(0.0001, 0.00001, lower=0)		
Dystocia, morbidity, and post-neonatal period to weaning	Normal	(0.001, 0.0001, lower=0)		
No dystocia, no morbidity, and post-neonatal period to weaning	Normal	(0.0001, 0.00001, lower=0)		
No dystocia, morbidity, and post-neonatal period to weaning	Normal	(0.0005, 0.0001, lower=0)		

Table 3.A1.22 (*cont.*). Morbidity and mortality.

Model Parameter	Distribution Type	Distribution Parameters	Reference	Notes
Daily probability of postweaning mortality			USDA (2010), and expert opinion	
Dystocia at birth	Normal	(0.00005, 0.00001,lower=0)		
No Dystocia at birth	Normal	(0.000025, 0.00001,lower=0)		
Daily probability of mature mortality	Normal	(0.000025, 0.00001,lower=0)	USDA (2010), and expert opinion	
Percent reduction in WW from morbidity	Normal	(0.065, 0.0065)	Wittum et al. (1994)	Applied to each calf individually

Table 3.A1.23. Calf growth.

Model Parameter	**Distribution Type**	**Distribution Parameters**	**Reference**	**Notes**
Calf birthweights				
Bull calf, two-year-old dam mean birthweight adjustment (kg)	Deterministic	-3.63	BIF (2010)	
Bull calf, three-year-old dam mean birthweight adjustment (kg)	Deterministic	-2.27	BIF (2010)	
Bull calf, four-year-old dam mean birthweight adjustment (kg)	Deterministic	-0.91	BIF (2010)	
Bull calf, eleven-year-old and older dam mean birthweight adjustment (kg)	Deterministic	-1.36	BIF (2010)	

Table 3.A1.24 (*cont.*). Calf growth.

Model Parameter	**Distribution Type**	**Distribution Parameters**	**Reference**	**Notes**
Calf birthweights				
Heifer calf, two-year-old dam mean birthweight adjustment (kg)	Deterministic	-3.17	BIF (2010)	
Heifer calf, three-year-old dam mean birthweight adjustment (kg)	Deterministic	-2.27	BIF (2010)	
Heifer calf, four-year-old dam mean birthweight adjustment (kg)	Deterministic	-0.91	BIF (2010)	
Heifer calf, eleven-year-old and older dam mean birthweight adjustment (kg)	Deterministic	-1.36	BIF (2010)	

Table 3.A1.25. Effective annual interest rates

Year	Effective Annual Interest Rate Non-Real Estate Agricultural Loans (percent)
2000	9.7
2001	7.8
2002	5.9
2003	5.4
2004	5.4
2005	6.7
2006	8.2
2007	8.3
2008	5.6
2009	4.8
2010	4.9
2011	4.4
2012	4.3
2013	4.1
2014	3.8
2015	3.8
2016	4.0
2017	4.4
2018	5.0*

From FED (2019)
*estimate

Appendix 3.2: Model Output

Percent Pregnant at Diagnosis

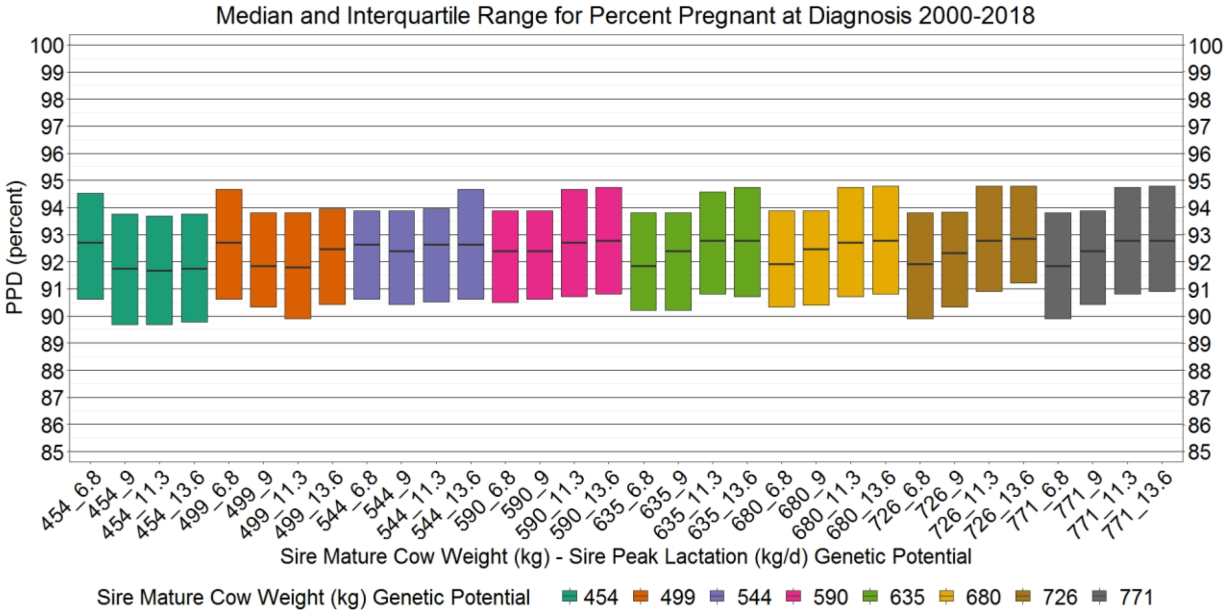

Figure 3.A2.1. Boxplots representing the median, 25th percentile, and 75th percentile of PPD aggregated across all iterations and production years 2000 through 2018 for each MW and PL category combination.

Weaning Age

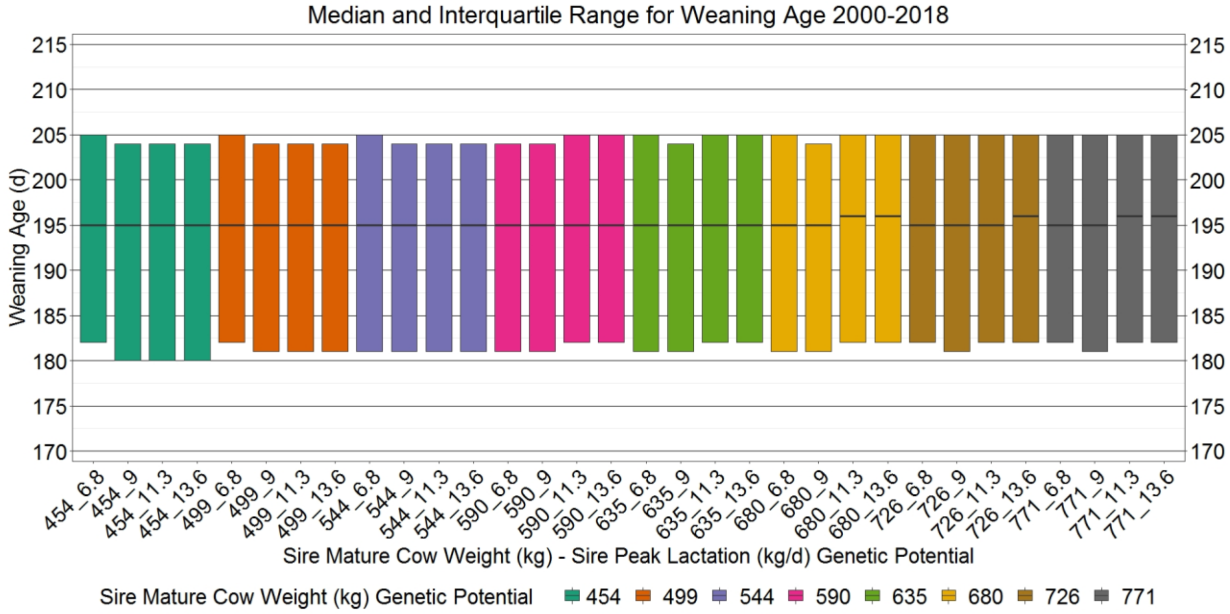

Figure 3.A2.2. Boxplots representing the median, 25th percentile, and 75th percentile of weaning age aggregated across all iterations and production years 2000 through 2018 for each MW and PL category combination.

Forage Production

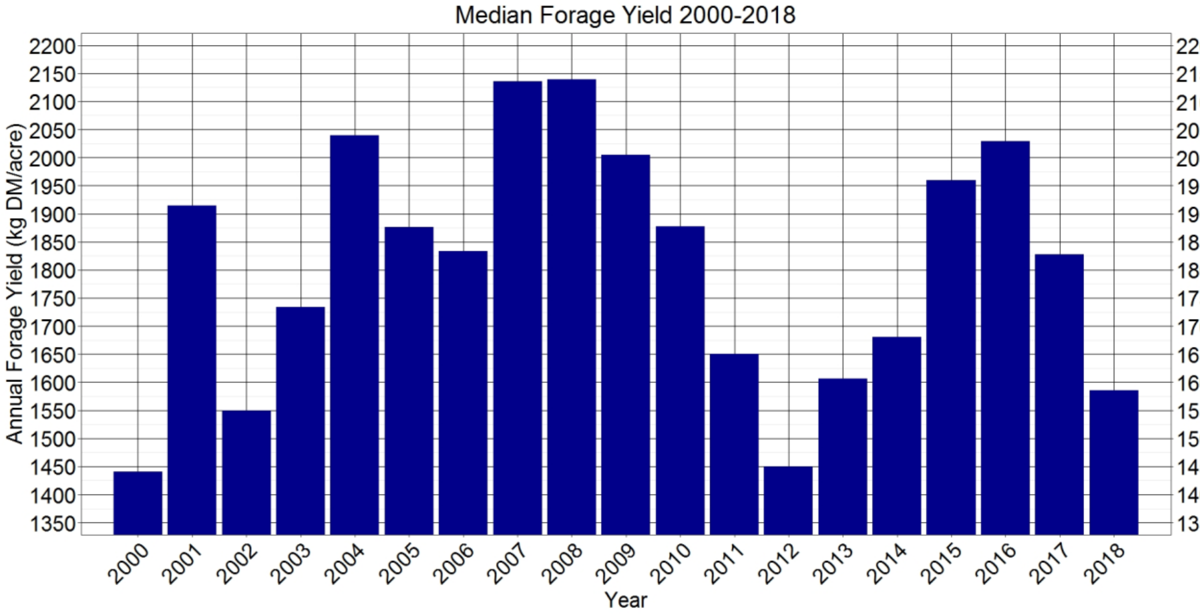

Figure 3.A2.3. Columns represent the median forage yield across all MW and PL category combinations and iterations for each production year 2000 through 2018.

Kilograms Weaned per Cow Exposed

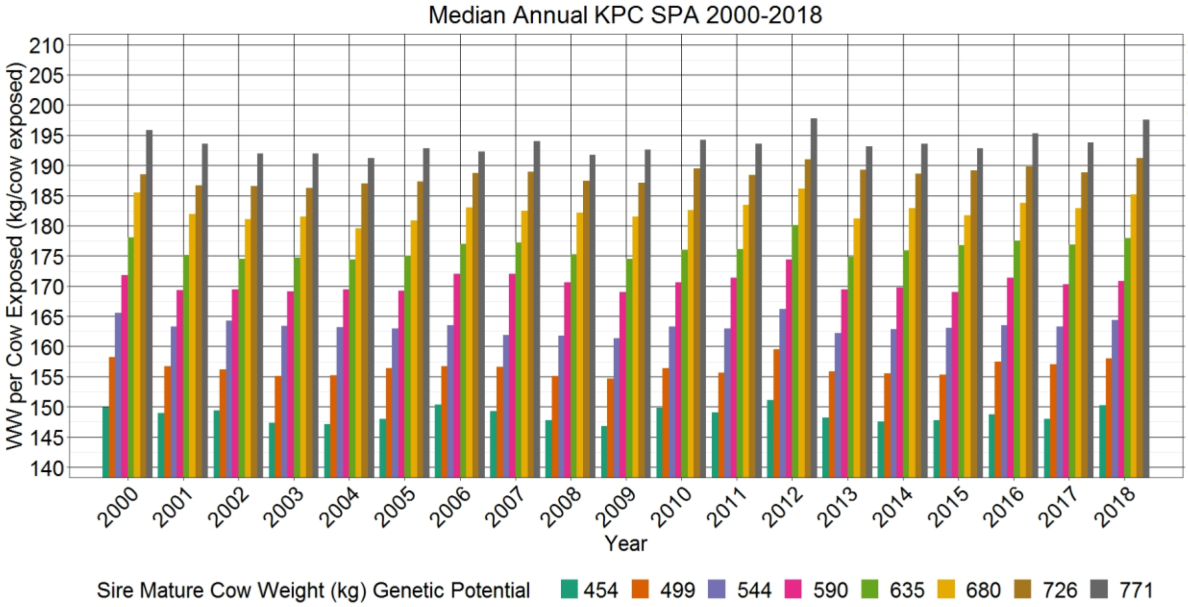

Figure 3.A2.4. Median KPC SPA by MW category across all iterations for each production year from 2000 through 2018.

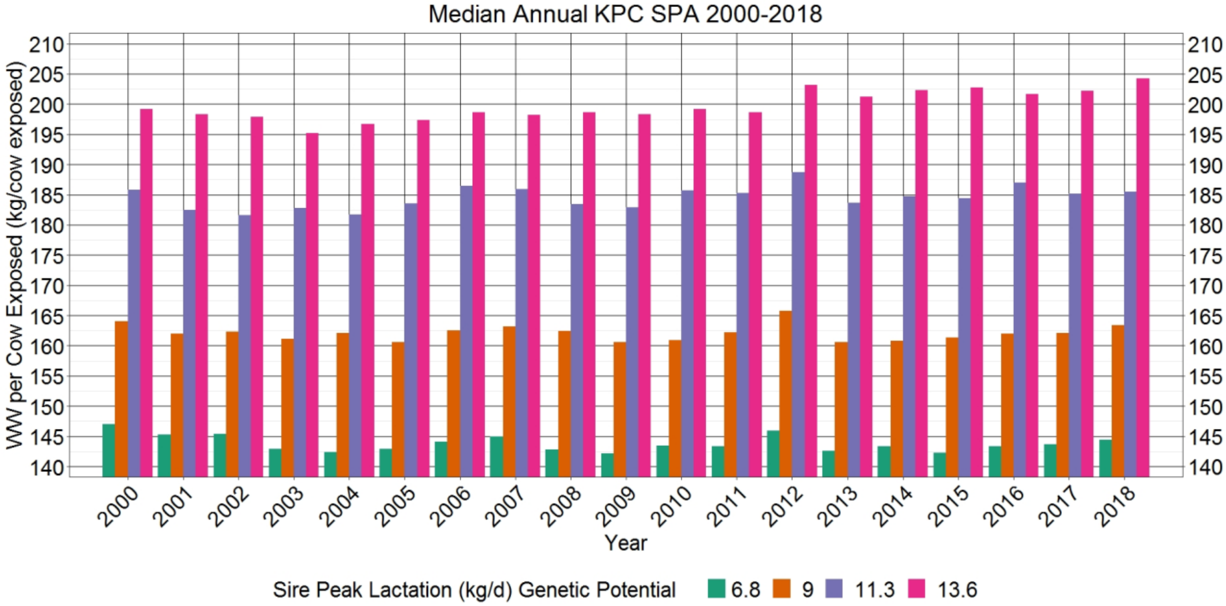

Figure 3.A2.5. Median KPC SPA by PL category across all iterations for each production year from 2000 through 2018.

Weaning Weight

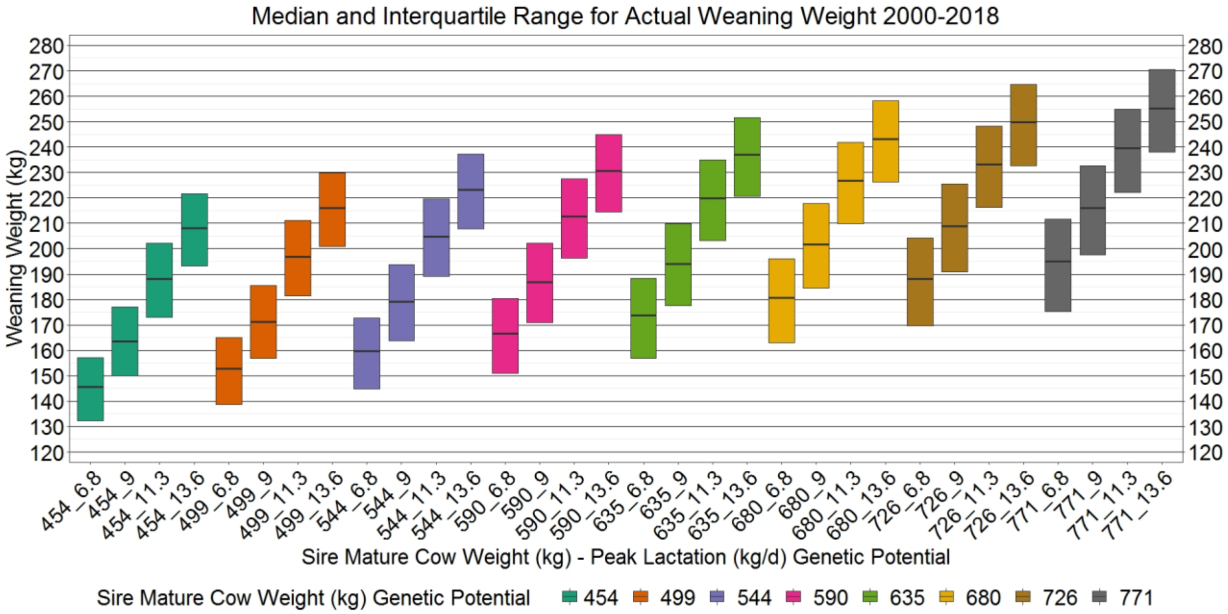

Figure 3.A2.6. Boxplots representing the median, 25th percentile, and 75th percentile of actual weaning weight aggregated across all iterations and production years 2000 through 2018 for each MW and PL category combination.

Table 3.A2.1. Median actual calf WW aggregated across all iterations and production years 2000 through 2018 by MW category.

Sire Mature Cow Weight (kg) Genetic Potential	Median Actual Calf WW (kg)	Median WW Change from Immediately Lighter MW Category (kg)
454	174.28	
499	182.59	+8.31
544	190.41	+7.82
590	198.20	+7.79
635	205.43	+7.23
680	212.57	+7.14
726	219.67	+7.10
771	226.24	+6.57

Table 3.A2.2. Median actual calf WW aggregated across all iterations and production years 2000 through 2018 by PL category.

Sire Peak Lactation (kg/d) Genetic Potential	Median Actual Calf WW (kg)	Median WW Change from Immediately Reduced PL Category (kg)
6.8	167.64	
9	189.85	+22.21
11.3	217.48	+27.63
13.6	231.78	+14.30

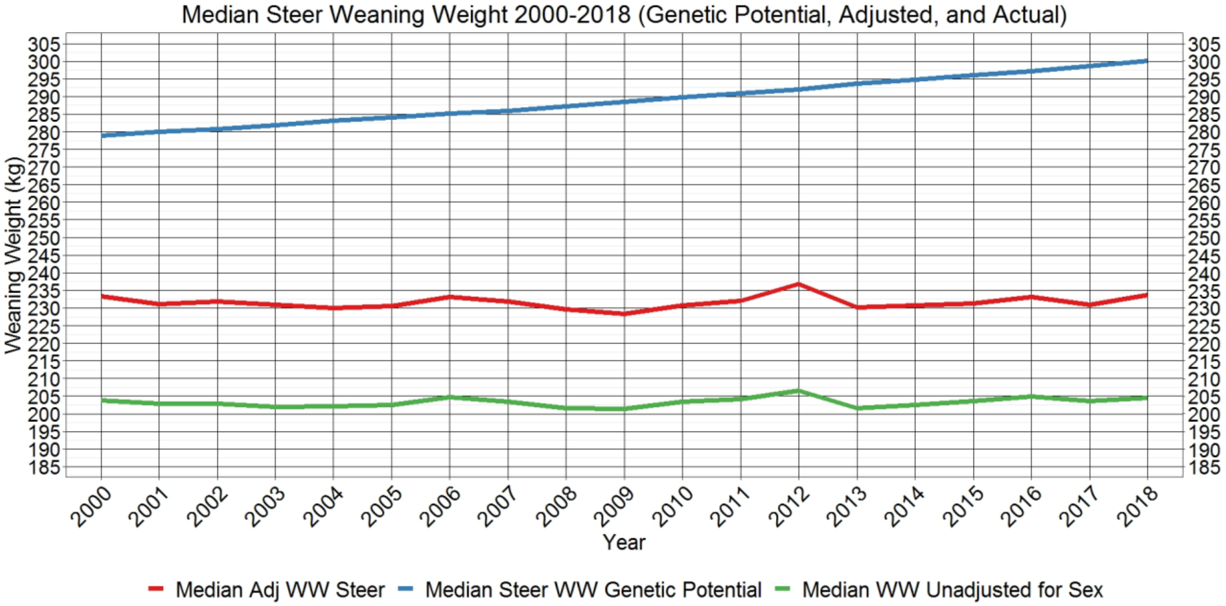

Figure 3.A2.7. Median adjusted WW on a steer base, median steer WW genetic potential, and median actual WW unadjusted for sex across all MW and PL category combinations and iterations for production years 2000 through 2018.

Kilograms Weaned per Hundred NEm Intake

Table 3.A2.3. Median KW NEmH aggregated across all iterations and production years 2000 through 2018 by MW category.

Sire Mature Cow Weight (kg) Genetic Potential	Median KW NEmH (kg/100 Mcal)	Median KW NEmH Change from Immediately Lighter MW Category (kg/100 Mcal)
454	3.01	
499	3.01	0.00
544	3.00	-0.01
590	2.99	-0.01
635	2.97	-0.02
680	2.95	-0.02
726	2.94	-0.01
771	2.93	-0.01

Table 3.A2.4. Median NEmH aggregated across all iterations and production years 2000 through 2018 by PL category.

Sire Peak Lactation (kg/d) Genetic Potential	Median KW NEmH (kg/100 Mcal)	Median KW NEmH Change from Immediately Reduced PL Category (kg/100 Mcal)
6.8	2.73	
9	2.88	+0.15
11.3	3.09	+0.21
13.6	3.16	+0.07

Annual Return per Breeding Female

Table 3.A2.5. Median and interquartile range for annual return per breeding female aggregated across all iterations and production years 2000 through 2018 by MW category.

Sire Mature Cow Weight (kg) Genetic Potential	Median Annual Return per Breeding Female (USD/cow)	Median Annual Return per Breeding Female Change from Immediately Lighter MW Category (USD/cow)	Interquartile Range: Annual Return per Breeding Female (USD/cow)
454	18.22		146.30
499	18.86	+0.64	155.45
544	14.90	-3.96	163.21
590	13.51	-1.39	168.42
635	11.12	-2.39	175.58
680	9.95	-1.17	184.16
726	4.88	-5.07	190.60
771	4.11	-0.77	200.54

Table 3.A2.6. Median and interquartile range annual return per breeding female aggregated across all iterations and production years 2000 through 2018 by PL category.

Sire Peak Lactation (kg/d) Genetic Potential	Median Annual Return per Breeding Female (USD/cow)	Median Annual Return per Breeding Female Change from Immediately Reduced PL Category (USD/cow)	Interquartile Range: Annual Return per Breeding Female (USD/cow)
6.8	-2.47		155.48
9	1.43	+3.90	166.68
11.3	22.49	+21.06	182.42
13.6	29.62	+7.13	193.90

Annual Return per Grazing Acre

Table 3.A2.7. Median and interquartile range for annual return per grazing acre aggregated across all iterations and production years 2000 through 2018 by MW category.

Sire Mature Cow Weight (kg) Genetic Potential	Median Annual Return per Grazing Acre (USD/acre)	Median Annual Return per Grazing Acre Change from Immediately Lighter MW Category (USD/acre)	Interquartile Range: Annual Return per Grazing Acre (USD/acre)
454	3.09		24.73
499	2.93	-0.16	24.36
544	2.22	-0.71	24.15
590	1.89	-0.33	23.40
635	1.47	-0.42	23.07
680	1.24	-0.23	22.99
726	0.57	-0.67	22.62
771	0.48	-0.09	22.78

Table 3.A2.8. Median and interquartile range for annual return per grazing acre aggregated across all iterations and production years 2000 through 2018 by PL category.

Sire Peak Lactation (kg/d) Genetic Potential	Median Annual Return per Grazing Acre (USD/acre)	Median Annual Return per Grazing Acre Change from Immediately Reduced PL Category (USD/acre)	Interquartile Range: Annual Return per Grazing Acre (USD/acre)
6.8	-0.34		21.56
9	0.21	+0.55	22.97
11.3	3.10	+2.89	24.75
13.6	4.11	+1.01	25.99

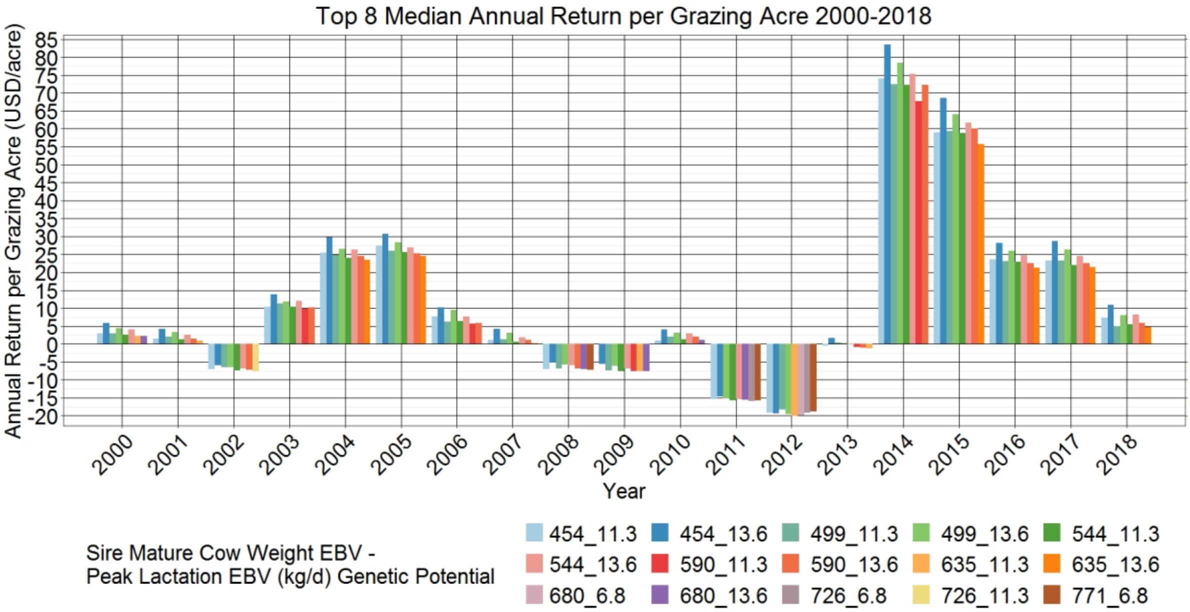

Figure 3.A2.8. Columns represent the top eight (25%) MW and PL category combinations across all iterations ranked by median return per grazing acre for each production year from 2000 through 2018.

Return on Investment

Table 3.A2.9. Median and interquartile range for annual ROI aggregated across all iterations and production years 2000 through 2018 by MW category.

Sire Mature Cow Weight (kg) Genetic Potential	Median Annual ROI (percent) (USD/USD)	Median Annual ROI Change from Immediately Lighter MW Category (percentage point) (USD/USD)	Interquartile Range: Annual ROI (percentage point) (USD/USD)
454	3.97		33.4
499	3.69	-0.28	33.4
544	2.84	-0.85	33.2
590	2.48	-0.36	32.3
635	2.07	-0.41	32.3
680	1.64	-0.43	32.6
726	0.79	-0.85	32.2
771	0.65	-0.14	32.5

Table 3.A2.10. Median and interquartile range for annual ROI aggregated across all iterations and production years 2000 through 2018 by PL category.

Sire Peak Lactation (kg/d) Genetic Potential	**Median Annual ROI (percent) (USD/USD)**	**Median Annual ROI Change from Immediately Reduced PL Category (percentage point) (USD/USD)**	**Interquartile Range: Annual ROI (percentage point) (USD/USD)**
6.8	-0.50		31.4
9	0.28	+0.78	32.0
11.3	4.04	+3.76	33.4
13.6	5.14	+1.10	34.5

Table 3.A2.11. MW and PL category combinations across all iterations and production years 2000 through 2018 ranked by median ROI assuming all simulated MW and PL combinations exist and no price differentiation between calves from different MW breeding systems.

Sire Mature Cow Weight (kg)-Sire Peak Lactation (kg/d) Genetic Potential	Median Annual ROI (percent) (USD/USD)	Median Annual ROI Change Between Rankings (percentage point) (USD/USD)	Median Annual ROI Rank
454_13.6	8.90		1
499_13.6	7.44	-1.46	2
544_13.6	7.00	-0.44	3
454_11.3	5.62	-1.38	4
499_11.3	5.42	-0.20	5
590_13.6	5.12	-0.30	6
544_11.3	5.05	-0.07	7
635_13.6	4.27	-0.78	8
590_11.3	4.25	-0.02	9
680_13.6	4.20	-0.05	10
635_11.3	4.14	-0.06	11
680_11.3	3.23	-0.91	12
726_11.3	2.08	-1.15	13
771_11.3	2.05	-0.03	14
726_13.6	2.04	-0.01	15
499_9	1.74	-0.30	16
771_13.6	1.59	-0.15	17
454_9	1.45	-0.14	18
590_9	0.41	-1.04	19
635_9	0.21	-0.20	20
544_9	0.19	-0.02	21

Table 3.A2.12 (*cont.*). MW and PL category combinations across all iterations and production years 2000 through 2018 ranked by median ROI assuming all simulated MW and PL combinations exist and no price differentiation between calves from different MW breeding systems.

Sire Mature Cow Weight (kg)-Sire Peak Lactation (kg/d) Genetic Potential	**Median Annual ROI (percent) (USD/USD)**	**Median Annual ROI Change Between Rankings (percentage point) (USD/USD)**	**Median Annual ROI Rank**
771_6.8	-0.09	-0.28	22
680_9	-0.18	-0.09	23
726_9	-0.23	-0.05	24
726_6.8	-0.34	-0.11	25
635_6.8	-0.45	-0.11	26
590_6.8	-0.48	-0.03	27
454_6.8	-0.50	-0.02	28
499_6.8	-0.53	-0.03	29
680_6.8	-0.66	-0.13	30
771_9	-1.00	-0.34	31
544_6.8	-1.01	-0.01	32

Table 3.A2.13. MW and PL category combinations across all iterations and production years 2000 through 2018 ranked by median ROI assuming 454 kg MW-13.6 kg/d PL and 499 kg MW-13.6 kg/d PL cows do not exist, and applying a $0.13/kg discount to the remaining 454 kg MW categories.

Sire Mature Cow Weight (kg)-Sire Peak Lactation (kg/d) Genetic Potential	Median Annual ROI (percent) (USD/USD)	Median Annual ROI Change Between Rankings (percentage point) (USD/USD)	Median Annual ROI Rank
544_13.6	7.00		1
499_11.3	5.42	-1.58	2
590_13.6	5.12	-0.30	3
544_11.3	5.05	-0.07	4
635_13.6	4.27	-0.78	5
590_11.3	4.25	-0.02	6
680_13.6	4.20	-0.05	7
635_11.3	4.14	-0.06	8
680_11.3	3.23	-0.91	9
726_11.3	2.08	-1.15	10
771_11.3	2.05	-0.03	11
726_13.6	2.04	-0.01	12
499_9	1.74	-0.30	13
771_13.6	1.59	-0.15	14
454_11.3	1.20	-0.39	15
590_9	0.41	-0.79	16
635_9	0.21	-0.20	17
544_9	0.19	-0.02	18

Table 3.A2.14 (*cont.*). MW and PL category combinations across all iterations and production years 2000 through 2018 ranked by median ROI assuming 454 kg MW-13.6 kg/d PL and 499 kg MW-13.6 kg/d PL cows do not exist, and applying a $0.13/kg discount to the remaining 454 kg MW categories.

Sire Mature Cow Weight (kg)-Sire Peak Lactation (kg/d) Genetic Potential	Median Annual ROI (percent) (USD/USD)	Median Annual ROI Change Between Rankings (percentage point) (USD/USD)	Median Annual ROI Rank
771_6.8	-0.09	-0.28	19
680_9	-0.18	-0.09	20
726_9	-0.23	-0.05	21
726_6.8	-0.34	-0.11	22
635_6.8	-0.45	-0.11	23
590_6.8	-0.48	-0.03	24
499_6.8	-0.53	-0.05	25
680_6.8	-0.66	-0.13	26
771_9	-1.00	-0.34	27
544_6.8	-1.01	-0.01	28
454_9	-2.49	-1.48	29
454_6.8	-4.22	-1.73	30

Revenue per Cow

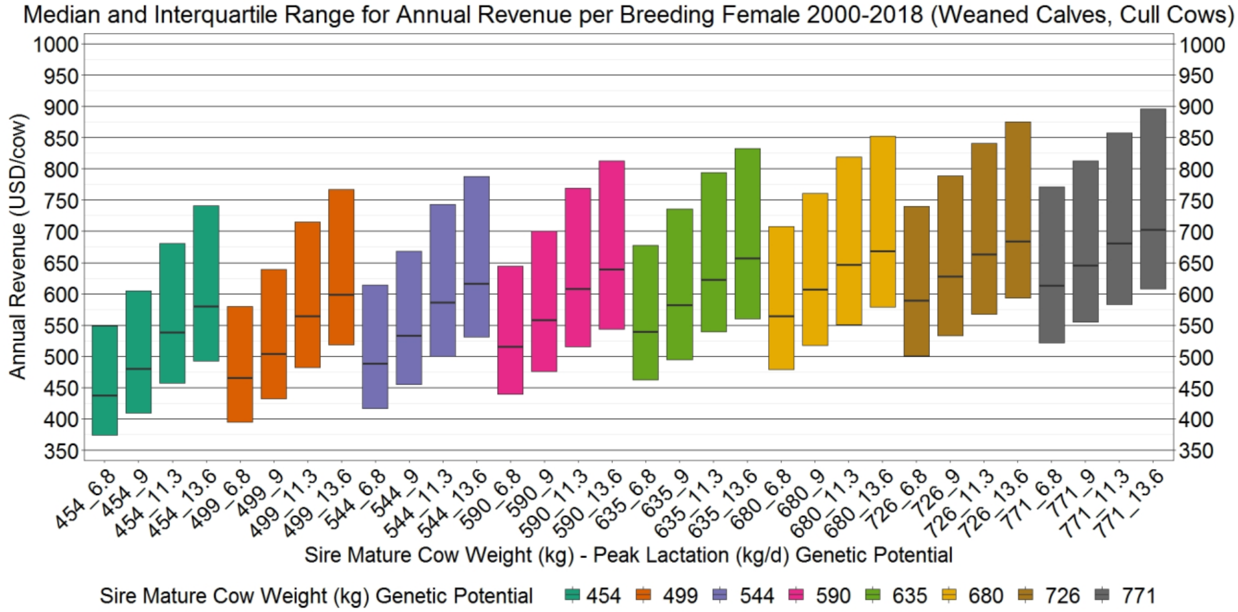

Figure 3.A2.9. Boxplots representing the median, 25th percentile, and 75th percentile of annual revenue per cow aggregated across all iterations and production years 2000 through 2018 for each MW and PL category combination.

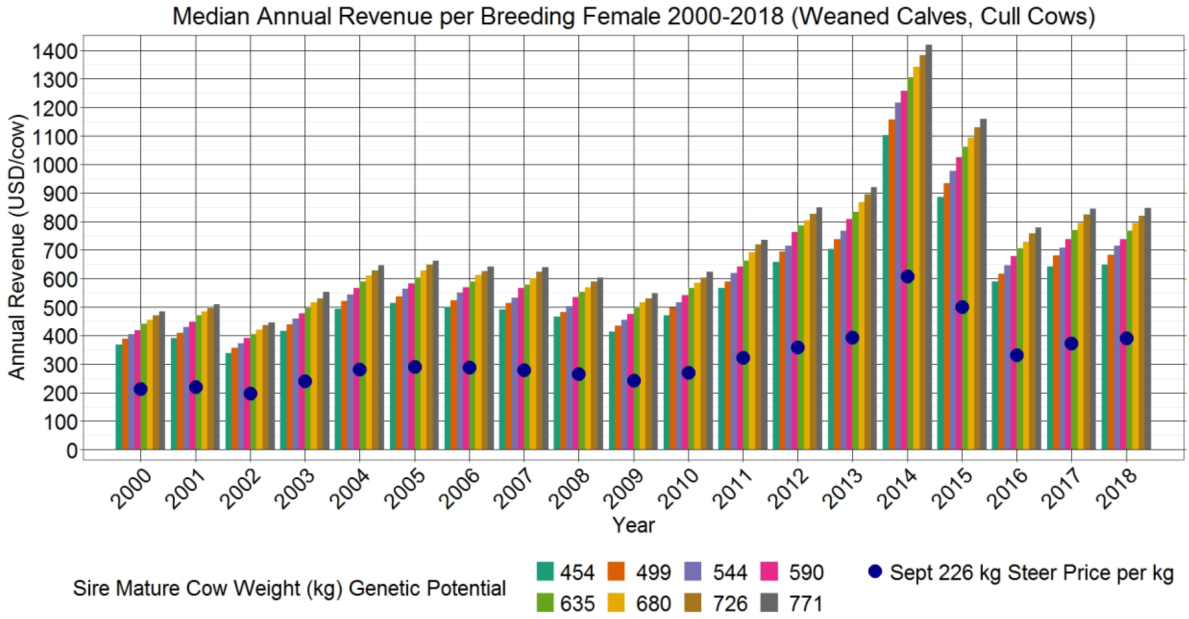

Figure 3.A2.10. Columns represent the median revenue per breeding female by MW category across all iterations for each production year from 2000 through 2018. Dots represent the September price per kg for a 226 kg steer for each production year. Cattle prices are exogenous variables based on historical data.

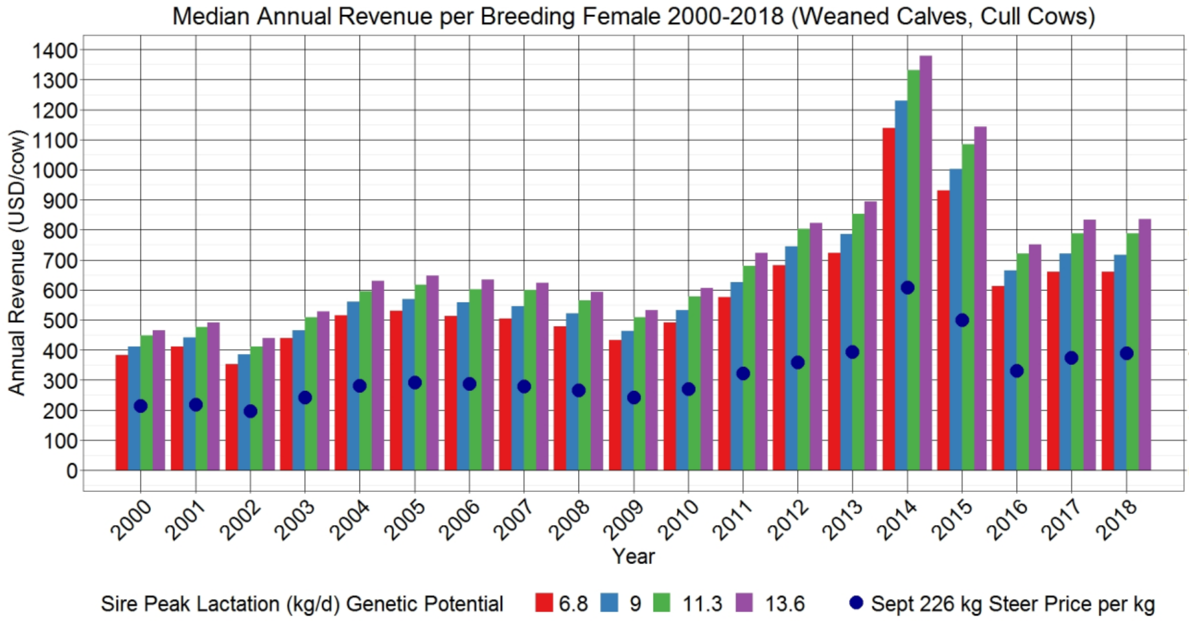

Figure 3.A2.11. Columns represent the median revenue per breeding female by PL category across all iterations for each production year from 2000 through 2018. Dots represent the September price per kg for a 226 kg steer for each production year. Cattle prices are exogenous variables based on historical data.

Variable Expense per Cow

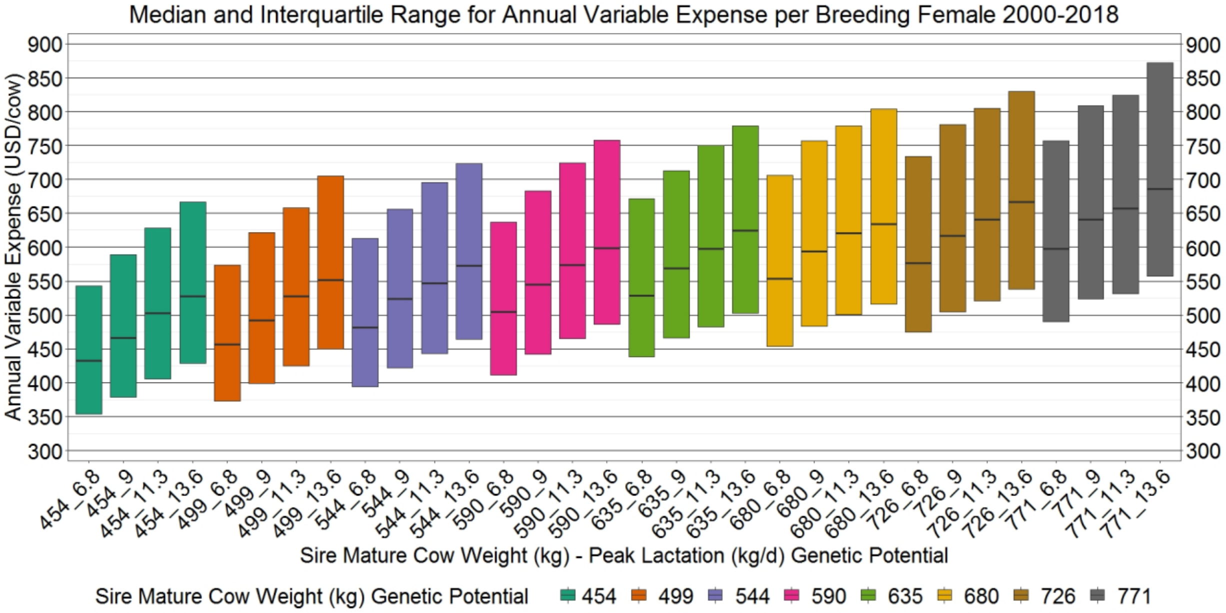

Figure 3.A2.12. Boxplots representing the median, 25th percentile, and 75th percentile of annual variable expense per cow aggregated across all iterations and production years 2000 through 2018 for each MW and PL category combination.

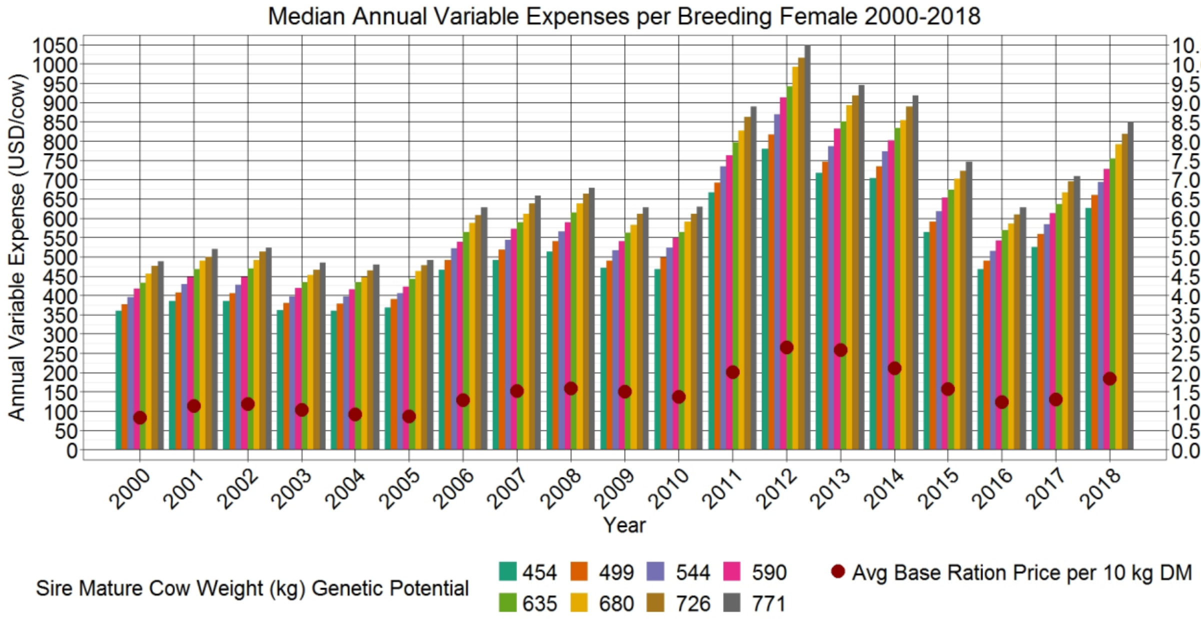

Figure 3.A2.13. Columns represent the median variable expense per breeding female by MW category across all iterations for each production year from 2000 through 2018. Dots represent the September price per kg for a 226 kg steer for each production year. Cattle prices are exogenous variables based on historical data.

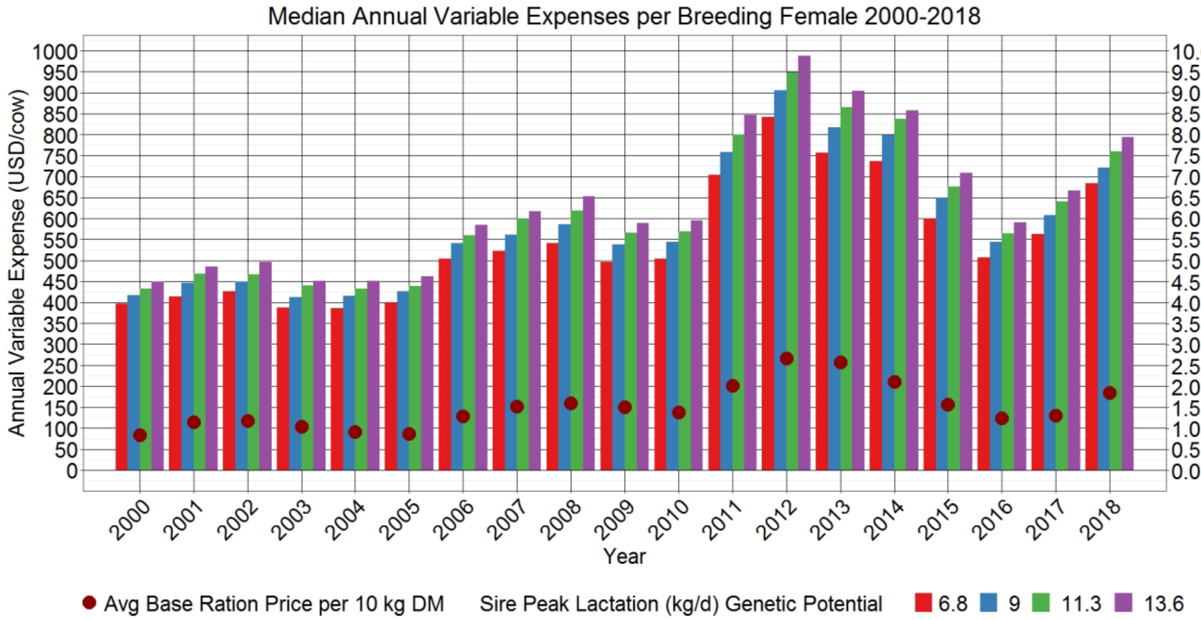

Figure 3.A2.14. Columns represent the median variable expense per breeding female by PL category across all iterations for each production year from 2000 through 2018. Dots represent the September price per kg for a 226 kg steer for each production year. Cattle prices are exogenous variables based on historical data.