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Application of Models in Feedlot Systems: Maintenance Energy Requirements, Growth and Cost Curves, and Feeding Behavior

Author
Harrison, Meredith

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Application of Models in Feedlot Systems: Maintenance Energy Requirements, Growth and Cost Curves, and Feeding Behavior

By

MEREDITH ANN HARRISON

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Approved:

James W. Oltjen, Chair

Roberto D. Sainz

Pedro H. V. Carvalho

Committee in Charge

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ABSTRACT

Emerging precision livestock technologies can collect real-time data on individual animal feed intake and body weights in feedlot production systems. With this individual animal data, feedlot producers are transitioning towards managing and marketing animals individually to improve efficiency, carcass uniformity, and profitability. Accurate prediction of feedlot cattle growth and body composition is necessary for optimal management and marketing of feedlot cattle. Broadly, this paper will evaluate the application of Davis Growth Model (DGM) for predicting maintenance energy requirements, growth, and economic returns in feedlot systems. One hundred and twenty Angus-cross steers (initial body weight = 348 ± 25 kg) were allocated into two feeding groups: 1) 24 steers fed individually using Insentec, Roughage Intake Control (RIC) feed bunks, and 2) 96 steers fed using conventional concrete bunks (CON). Steers in the CON group were sorted by either body weight (i.e., light and heavy) or expected days on feed (i.e., short and long) determined using the DGM. There were two replicates of each sort treatment, for a total of eight pens with twelve steers in each pen. Four of the eight CON pens were equipped with bunk cameras that captured images at one-minute intervals. All groups were fed a high concentrate finishing ration for a minimum of 84 d before harvest.

Measurements for body weight (BW), hip height, back fat thickness (BF), and ribeye area (REA) were taken at 28 d intervals while on the finishing ration. Feeding behavior was collected on RIC steers using radio frequency identification data from the Insentec system. Conventional steers in pens with cameras were uniquely identified using colored adhesive patches and trained observers reviewed the images and recorded feeding behavior for individual animals. Feeding behavior traits considered were total daily eating duration (ED), bunk visit (BV)

frequency, mean BV duration, meal frequency, mean meal duration, and total daily meal duration (MD). Repeated BW and composition measurements were used to create individual and pen-level growth curves for BW, empty body fat (EBF) percent, Yield Grade (YG), and Quality Grade (QG). The DGM was used to evaluate changes in maintenance energy requirements (alpha) and protein synthesis (K2) parameter estimates from the original values. Alpha was correlated with production parameters and feeding behavior measured using linear regression, and feeding behavior was compared between RIC and CON groups using regression analysis. Dry matter intake curves were developed on and individual and pen-basis for RIC and CON groups, respectively. Projections from the growth and DMI curves were used to generate marginal cost and revenue curves to estimate profitability and the optimal harvest day for individual RIC animals and CON pens. Effect of sorting by BW and days on feed (DOF) were evaluated using a *t*-test and an *F*-test to compare treatment means and variances, respectively.

Alpha and K2 have increased by 14.4 and 9.6% compared to the previous alpha and K2 estimates, suggesting increases in both apparent maintenance energy requirements and rates of protein synthesis. Steers with decreased maintenance energy requirements tended to be faster growing with increased rates of protein synthesis and greater EBF percent at harvest. Residual feed intake (RFI), DMI, SBW, and BF were able to explain 78% of the variation in alpha. Feeding behavior traits were not influential on alpha. Compared to the RIC cattle, CON steers had a smaller number of longer feeding bouts, increased ED, and decreased DMI. Cattle with low RFI tended to have increased BV frequency (P = 0.08), decreased mean BV duration (P = 0.02), and slower eating rates (P = 0.06). Results from the growth curves indicated BW, YG, and QG all increase with longer DOF, but marketing optimums vary based on grid prices and feed costs. Sorting by DOF improved carcass uniformity, decreased carcass discounts, and improved profitability. With individual animal growth trajectories, feedlot operators can make decisions regarding pen sorting, feed and health management, and marketing. By combining these models with DMI data, incremental cost of gain can be calculated, which can be used to pinpoint exact marketing optimums, and increase profitability by decreasing within pen variation, reducing overfeeding, and improving carcass uniformity.

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CHAPTER 1: REVIEW OF LITERATURE

INTRODUCTION

Modern United States feedlots are complex systems that combine animal nutrition, husbandry, genetics, agricultural engineering, and technology. Since the inception of feedlots in the mid 1900s, sustainability of beef cattle production has markedly improved in terms of resource use and animal efficiency. Between 1961 and 2018, the U.S. beef industry improved beef produced per animal by more than 66%, while simultaneously reducing methane emissions by over 40% (FAO, 2018; NASS, 2021). This progress in efficiency has been achieved through the industrialization of feedlots and the combined use of production technologies (e.g., antibiotics, vaccines, beta-agonists, growth implants), but the feedlot industry has modest beginnings.

Ranching cattle began in the post-civil war era, predominantly in the central southwest. Prior to this, cattle were typically more valuable for milk and cheese than they were for meat (Hubbs, 2010). In 1838 the John Deere steel plow was invented, streamlining grain production (Wagner et al., 2014). And in 1878, Augustus Swift successfully used a refrigerated railcar to ship meat in 1878, which allowed transportation of beef throughout the U.S. (Hubbs, 2010; Peel, 2021). By the 1930s, hybrid seed corn was developed, and deep well irrigation followed in the 1940s, which led to a surplus of grain and the commercialization of feedlots in the 'corn belt region,' where grain was inexpensive and plentiful (Wagner et al., 2014). Simultaneously, large feed mills were developing complex ration formulations, with the ability to process 200 to 500,000 tons of feed annually (Coffey et al., 2016). With these advancements, between 1940 and 1969, the number of cattle in the United States nearly doubled, eventually peaking at 132 million in 1975 (Coffey et al., 2016; Peel, 2021).

Despite a reduction in cattle numbers since then, beef production increased from 250 pounds per animal in 1950 to over 660 pounds per animal currently (Peel, 2021). Fertilizers and pesticides boosted grain production, while the advent of vaccines, antibiotics, hormonal implants, grain processing, and advanced ration formulations facilitated significant improvements in feedlot production efficiency. In 2021, beef production reached an all-time record of 27.9 billion pounds. This was 2.4% greater than the previous beef production record that was established in 2020, and 75% greater than beef production in 1976 when cattle harvest peaked (Peel, 2021; USDA, 2022).

Such achievements in beef production have been made possible through improvements in growth and feed efficiency. Predicting cattle growth is an intricate process, involving multiple estimates of energy, and dynamic measurements of body size and composition. Growth models are constrained by inaccurate feed intake measurements. To continue making progress toward production efficiency, feedlots producers must utilize cattle growth and dry matter intake (DMI) prediction models. The proliferation of growth models has been heightened with the emergence of precision livestock technologies (PLT); for example, sensors, cameras, and radio frequency identification. These technologies provide continuous, real-time data to inform prediction models and improve predictability to help producers make informed management and marketing decisions to continue the improvement of biological and economic efficiency of feedlot cattle production. Success in the modern feedlot industry will require progressive thinking and the combined adoption of PLT and advanced algorithms for predicting cattle growth and intake.

FEEDLOT CATTLE GROWTH MODELS

Historically cattle have been purchased, managed, and marketed as lots (i.e., pens), generally ranging between 150 and 250 animals per lot. However, as profit margins narrow, feedlot producers must use innovative strategies to manage and market cattle individually to improve profitability. Properly sorting (e.g., grouping cattle by BW) cattle has been shown to reduce variation within a pen and increase profitability (Smith et al., 1988; Sainz and Oltjen, 1994; Pyatt et al., 2005). With accurate knowledge of growth trajectories, cattle could be sorted to increase carcass uniformity, minimize carcass discounts, and reduce overfeeding. Accurate growth prediction is a multifarious process that requires precise quantification of intake energy and retained energy, which can widely vary depending on physiology, environment, and genetics. By combining growth models with new PLT and machine learning techniques, cattle growth models could reflect real-time changes in cattle growth and composition.

Energy. Retained energy (RE), or the amount of energy stored in tissue, can be expressed as a function of metabolizable energy (ME), where RE = ME – heat energy (HE). Garrett et al. (1959) pioneered the use of the comparative slaughter technique to estimate RE from cattle consuming known quantities of feed. The California Net Energy System (CNES), which serves as the basis for many of our growth prediction models, is based on RE values (Lofgreen and Garrett, 1968). Retained energy is estimated using known quantities of retained protein (RP) and retained fat (RF) measured at harvest. Net energy is partitioned into energy for maintenance (NE_m) and growth (NE_g) using RE and RP measurements. The CNES is used to estimate retained fat (RF) and empty body weight (EBW) gain to develop net energy feed values for use in ration formulation and subsequent growth prediction models that are still commonly used today (Lofgreen, 1965; Lofgreen and Garrett, 1968).

Metabolizable energy, rather than digestible energy, is the basis for the CNES, due to variation in gaseous energy (primarily CH_4) loss due to varying diets, level of intake, and animal age (Hales et al., 2022). Fasting heat production was determined using the comparative slaughter technique at University of California, Davis from 1960 to 1980 (Garrett, 1980, 1987), and the value of ME was determined:

$$ME = 0.82 \times \text{digestible energy (DE)}$$

This has been widely adopted for decades (NRC, 1976; NASEM, 2016), however the conversion of DE to ME may be more efficient with high grain diets (Hales et al., 2022). Vermorel and Bickel (1980) reported a range in ME:DE ratios from 0.82 to 0.93 in growing cattle. Recent research by Hales et al. (2022) based on regression models, suggested the equation:

$$ME = DE - 0.39 \text{ Mcal/kg}$$

Establishing correct ME values is critical because NE_m and NE_g, which are the basis for energy utilization and ration formulation, are calculated from ME (Ferrell and Oltjen, 2008). The relationship between ME intake and RE is curvilinear and the differing ME efficiencies for maintenance and gain are represented by separating net energy into NE_m and NE_g (Lofgreen and Garrett, 1968; Garrett, 1980). The differing slopes reflect differences in efficiency of energy use for maintenance and gain. Garrett (1980) reported equations for converting ME to NE_m and NE_g (Mcal/kg) that were subsequently adapted by the NRC (1984, 2000) and (NASEM, 2016).

These energy partitioning equations and assumptions are imperative to growth models as they are the basis for estimating protein and fat accretion.

Body fat. Growth equations are typically developed with EBW, which is assumed to be 89.1% of shrunk BW (Garrett, 1980; NASEM, 2016). Empirical regression equations were developed to relate empty body fat (EBF) to EBW across a variety of breeds from birth through maturity (Simpfendorfer, 1974). It is important to represent changes in composition over time because as an animal matures, a greater proportion of EBW is deposited as fat, with gain containing less additional protein. Owens et al. (1995) reported that protein accretion declined to zero when cattle reached their mature body size (about 36% EBF). With respect to growth prediction, EBF must be quantified, as energy requirements vary based on the proportion of fat in the gain (Fox and Black, 1984). Fox and Black (1984) expressed percent EBF quadratically as a function of EBW, and percent EBF was used to calculate the percentage of fat in the carcass, which was expressed in terms of carcass quality and yield grades (YG). Equations by Fox and Black (1984) were reported to work moderately well for commercial feedlot cattle, with YG equations performing better than quality grade (QG) equations due to the fact percent EBF insufficiently described marbling distribution (Fox and Black, 1984; Perry and Fox, 1997; Guiroy et al., 2001). The relationship between EBF and marbling remains of practical importance because many growth models utilize percent EBF as a proxy for marbling score, but publications correlating percent EBF to marbling are limited.

Simpfendorfer (1974) concluded the main driver of variation in chemical composition among cattle of similar mature size was EBW. These results are consistent with NASEM (2016), where the exponent on EBW gain$^{1.097}$ indicates the energy content of gain increases as rate of gain increases, regardless of EBW (NASEM, 2016). Krehbiel et al. (2006) reported the proportion of fat and protein in gain is dependent on dietary ME, with greater concentrations of dietary ME corresponding to increased proportions of fat in gain. However, as Owen et al. (1995) highlighted, relationships of weight gain and proportion fat and protein in gain are confounded by BW because cattle are typically harvested based on a specified days on feed rather than a constant BW. The relationship between body composition and mature EBW reported by Simpfendorfer (1974) has subsequently been confirmed in two additional studies (Tedeschi et al., 2004; Tedeschi and Fox, 2018).

It has been established that depending on frame and mature size, cattle reach the same chemical composition at varying BW (Fortin et al., 1980). Given this, cattle and equations should only be compared at a given body composition, rather than a given BW. The NRC (1984) equations contain a scaling factor to adjust for BW differences at a given body composition. A standard reference BW for varying final body compositions was developed by the Commonwealth Scientific and Industrial Research Organization (CSIRO, 1990; Tylutki et al., 1994; CSIRO, 2007). An EBF percent of 28%, corresponds to a USDA QG of low choice and a standard reference weight of 478 kg (CSIRO, 1990; Perry and Fox, 1997). These equations were subsequently validated using carcass measurements, and USDA low choice was determined to correspond to an empty body fat of 28.6% (Guiroy et al., 2001; NASEM, 2016). Considering that those relationships were determined decades ago, and that beef cattle hot carcass weights (HCW) and marbling have since substantially increased (NCBA, 2017), the relationship between percent EBF, standard reference weights, and QG should be reassessed with modern cattle.

To accurately predict animal performance, growth equations were further adjusted to account for breeds, frame size, implant status, and body condition due to previous nutrition. Net energy multipliers were established to increase energy for smaller frame size, decreased body fatness, and prolonged cold environmental stress (Fox and Black, 1984; Fox et al., 1992). Efficiency of growth is improved with the use of ionophores and growth implants. The use of growth implants increased mature BW at which 28% empty body fat was achieved (Garrett, 1980; Fox and Black, 1984). Feeding ionophores has been reported to increase dietary NE_m from 3 to 12% (Zinn, 1988; Tedeschi et al., 2003; NASEM, 2016). With additional energy adjustments, growth models have expanded and increased in complexity.

Growth models. The development of fundamental equations relating energy partitioning and body composition allowed for the proliferation of a variety of growth models in the 1980s and 90s. The Texas A&M Cattle Systems Production Model (Sanders and Cartwright, 1979a,b) was a deterministic, whole system model for simulating beef production efficiency. The model used a Brody curve in the growth subroutine, where animal requirements were calculated on a TDN basis. However, a more sophisticated animal-level model was required for accurate growth production. Notter et al. (1979) expanded the A&M Model, applying Taylor's (1980) size scaling rules to adjust for differing mature BW and applied feed intake equations from the NRC (1984).

Oltjen et al. (1986a, b) developed a dynamic growth model (Davis Growth Model; DGM) to predict protein accretion based on concepts of hyperplasia and hypertrophy, using DNA as a proxy for cell numbers at initial and mature BW. The combined animal and tissue-level model integrated differential equations to estimate BW and protein gain, and EBF gain was estimated as residual net energy after energy for maintenance and protein gain was met. Empirical relationships between whole body DNA, fat, protein, animal BW, mature size, and condition score were used to determine initial values for implementation. Although no bias was present with respect to composition, frame, or energy intake, the DGM underpredicted fat gain on high energy rations (Oltjen et al., 1986b).

Equations used in the DGM were expanded and used to predict pools of body and viscera protein and the associated DNA and fat pools (Di Marco et al., 1989). This extended model was combined with digestion and metabolic models to measure energy balance. Cianzo et al. (1985) indicated that this approach could be used to evaluate adipose mass using cell number and size to predict marbling. Hoch and Agabriel (2004) applied this approach and simulated two body fat pools—carcass and non-carcass lipids—in addition to body and viscera protein pools. To keep the model simple, DNA was not considered as a state variable. However, the final model lacked parsimony, including 26 parameters, which contributed to uncertainty and error (Hoch and Agabriel, 2004).

During this same time, the empirical French system (INRA, 1989) was developed at Institut National de la Recherche Agronomique. Gompertz growth curves were used with BW data for different continental breeds (Robelin and Daenicke, 1980). Composition of gain was determined using allometric equations and energy requirements for growing cattle reported by the NRC (1996). In an assessment of the INRA model, Arnold and Bennett (1991) described the model as simplistic and requiring a more dynamic approach to evaluate nutritional changes. Growth curves from Notter et al. (1979) and Oltjen et al. (1986b) were compared, and similar final BW were reported, although weight gain was more rapid using the DGM. With both models, increased DMI contributed to increased body fatness, but the DGM relied on observed DMI data, as DMI prediction was not a model component (Arnold and Bennett, 1991).

The Cornell Net Carbohydrate and Protein System (CNCPS) used the same approach as Notter et al. (1979), basing the model on TDN, rather than ME (Fox et al., 1992; Russell et al., 1992; Sniffen et al., 1992). The CNCPS was created to predict nutrient requirements, DMI, and nutrient utilization in beef cattle using a simple ruminal fermentation model to predict passage and degradation rates and determine the amount of TDN and protein to the animal. Dietary TDN was converted to ME and partitioned into NE_m and NE_g using NRC (1984) equations. This model was subsequently expanded and used to create a mechanistic dynamic model for cattle growth (Tedeschi et al., 2004).

The model described by Tedeschi et al. (2004) dynamically predicted growth rate, accumulated BW, and days required to reach a specified end composition. The model requires a user-input for BW at a known composition and dietary energy to compute equivalent shrunk BW. It uses an iterative approach to either calculate ADG with a known DMI or calculate DMI using a known ADG. When DMI was known, ADG and final shrunk body weight (SBW) were predicted well, however EBF predictions were less than expected (R^2 = 0.61). With a known mean BW and ADG, dry matter required and EBF were both accurately predicted (Tedeschi et al., 2004).

Subsequent modifications to the described models have improved their functionality. However, all the growth models have their advantages and disadvantages. Oltjen (1993) suggested a need to shift toward mechanistic models, where body components are considered state variables, and a dynamic approach is applied to simulate changes in composition in response to available energy. Conversely, using mechanistic models to predict growth is challenging, as the number of state variables, equations, and parameters must be sufficient to describe the system but not be overly complex (Hoch and Agabriel, 2002). Ferrell and Oltjen (2008) recommended the continued evolution of existing models and quantification of inherent growth variation within animals and due to ration effects.

Model evaluation. The NRC (1996, 2000) and DGM were evaluated by NASEM (2016) using three independent data sets, and it was reported the NRC model accounted for more variation and has less bias than the DGM. Equations deriving final SBW from final EBF had an R^2 = 0.72 with a bias of -2% (NASEM, 2016). A second evaluation by Tedeschi (2019) used seven independent studies and reported use of the NASEM (2016) equations resulted in an unfavorable correlation between observed and expected RP (r = 0.86), but an anticipated relationship (r = 0.98) was reported for RE. The NASEM (2016) equations were fit using pen averages, so when equations were evaluated with individual animal data, both R^2 values further decreased (Tedeschi, 2019). Such results indicate a relatedness between RP and RE that impacts the ability to accurately predict RE with greater precision (Tedeschi and Fox, 2018; Tedeschi, 2019). These model errors suggest growth predictions may be compromised due to an inadequacy of the CNES, which is the basis for most beef cattle growth models.

Tedeschi (2019) stated the error could come from the difference in partitioning ME efficiency losses using the carcass and diet approaches. A recent publication suggests equations from NASEM (2016), especially in growing animals, may underpredict the energy in current cattle rations (Cabezas-Garcia et al., 2021). The NASEM (2016) stated there was variation in ME values assigned to feeds due to varying feed composition, which contributes to variation in NE_m

and NE_g estimated from ME because of variation in end products of digestion and their rate of metabolism. As previously indicated, 0.82 may be too low of a conversion factor for converting DE to ME (Hales et al., 2022), which would underpredict the energy values used in the CNES and many foundational growth models.

A second practical problem is choosing the wrong final SBW. Previously, an EBF percent of 28% was accepted as a target percent EBF (Perry and Fox, 1997), but this may no longer be appropriate for modern, heavier cattle that are selected for high marbling. Choosing an incorrect final SBW will have impacts on maintenance energy adjustments. Final SBW depends on the animals mature BW, which is related to frame score (FS). Frame score equations that were developed in the 1970s may not be appropriate for modern cattle. Beef Improvement Federation FS equations were developed using hip height at a given age to calculate a numerical FS of 1 to 9 (Beef Improvement Federation, 2021). Buskirk (2020) highlights the weight to frame ratio of cattle has changed substantially. Based on Angus herd improvement records, FS has steadily decreased over the past 20 years, while average yearling weight has increased in the same time period. Emphasis has been placed on selecting cattle that are deeper and wider, and as such a FS of 5.5 for a yearling Angus bull is 150 pounds heavier today than a bull from the 1980s with the same frame size (Buskirk, 2020). The Beef Improvement Federation (2021) cautions use of FS stating, “predictions of expected carcass weights or mature cow weights based on FS that appear in many publications are likely incorrect today.” Further research and evaluation are needed to determine the appropriate adjustments to redefine the relationships between mature BW and FS.

It is critical to accurately quantify energy partitioning, as it is fundamental to calculating RE and making growth predictions. Relationships between RE and ME need to be better understood to accurately determine net energy for growth models. With new technologies, measuring heat production is feasible via indirect calorimetry. Similarly, systems can simultaneously monitor CH_4, which could be used to better estimate gaseous energy losses to improve estimates of ME. Some of the previous estimates and equations could be critically evaluated with a combination of these methodologies with the comparative slaughter technique. Further refinement of existing growth models would reduce error and bias to improve growth trajectories, which could be used as a decision support tool for producers.

PREDICTION OF DRY MATTER INTAKE

As profit margins narrow and environmental pressure intensifies, the application of new technologies to improve beef production productivity and efficiency is critical. Traditional breeding programs have approached efficiency by focusing on system outputs—traits like growth, carcass characteristics, and fertility—to improve profitability (Carstens and Tedeschi, 2006). Over the last several decades, this approach facilitated massive improvements in production efficiency. However, sizable opportunity for improved efficiency can be achieved through minimizing production costs. In feedlot systems, feed accounts for 70% of operational costs (Neilsen et al., 2013; Shike, 2013). Improving feed efficiency has substantial opportunities to advance both biological and economic efficiency of feedlot production.

Dry matter intake data are necessary for calculating feed conversion ratio (kg gain/kg DMI) and residual feed intake (RFI), which is the difference between actual and expected feed intake. Since RFI is moderately heritable and is independent of BW, it is a suitable candidate to make genetic progress toward feed efficiency (Arthur et al., 2001; Herd et al., 2003; Crowley et al., 2010; Kelley et al., 2020). Despite its high heritability and economic relevance, RFI is rarely considered in breeding programs due to the lack of DMI data available at a commercial level (Berry, 2008). Large scale DMI measurement will help researchers better understand phenotypic variation associated with DMI, which can help highlight inefficiencies and advance feed efficiency at a herd level (Kenny et al., 2018).

Accurate predictions of DMI are required to calculate nutrient requirements for feedlot cattle (NASEM, 2016). Further, DMI is of practical importance to feedlot producers, as it has been shown to affect cattle growth performance, BW and composition, time on feed, and methane emissions (Hicks et al., 1990; Sainz et al., 1995a; Schwartzkopf-Genswein et al., 2003; Van Lingen et al., 2019). Despite this, accurate prediction is challenging due to the multitude of complex mechanisms that control DMI in beef cattle (Tedeschi et al., 2004; Allen, 2014). Several recent models have evaluated DMI, but they were only able to account for 58 to 77% of variation in DMI (Anele et al., 2014; Herd et al., 2019). New camera and sensor technology may enable collection of data that provide opportunities to expand existing DMI prediction equations to account for feeding behavior and changes in body composition. Substantial opportunity exists for developing new accurate DMI prediction equations for beef cattle.

Intake control. Dry matter intake is impacted by energy demands for maintenance and gain; physiological constraints like rumen fill, ruminal pH and VFA concentrations; and hormonal cues (Tedeschi et al., 2004). Energy requirements are dictated by many of the principles previously discussed when describing growth models. Specifically, it has been well documented that body fatness affects feed intake. Fox et al. (1988) reported DMI decreased 2.7% for each 1% unit increase in EBF percent. This relationship is apparent in DMI equations, with DMI decreasing with increasing days on feed (DOF; Thornton et al., 1985; Hicks et al., 1990). Further, DMI differs among sexes, age, and physiological state and the previous plane of nutrition, which contributes to intake and compensatory gain (NASEM, 2016).

Environmental and dietary factors both play a large role in feed intake. The association between ambient temperature and DMI has been well documented. Prolonged cold stress will increase DMI (NRC, 1987), as cold weather requires more heat production to maintain body temperature, thus increasing metabolic rate (Fox and Tylutki, 1998). Conversely, heat stress, particularly a high temperature-humidity index, will cause a decrease in DMI to decrease energy intake and decease internal body heat loads (Gorniak et al., 2014; Chung-Fung-Martel et al., 2022). These changes in energy intake and partitioning have been accounted for in DMI prediction equations using multiplicative adjustment factors to correct for varying environmental effects (Fox et al., 1988). Hicks et al. (1990) developed DMI equations for feedlot steers by season to account for changes in environmental conditions. With respect to diet, forage-based diets decrease DMI compared to grain-based diets due to increased rumen fill. Arelovich et al. (2008) reported DMI decreased with increasing NDF (R^2 = 0.97). Growth hormone implants increase DMI (Fox et al., 1988; Rumsey et al., 1992); however, the NASEM (2016) cautions adjusting DMI prediction equations for implant status, as most DMI prediction models were developed using implanted cattle. Some may suggest decreasing DMI for non-use of implants. As previously stated, monensin increases available feed energy, but it has been documented to decrease DMI from 2 to 10% depending on the diet (Fox et al., 1988; Gaylean et al., 1992). Feed processing can also impact intake. Fine grinding forages will increase intake, but fine grinding of concentrates will decrease DMI, especially with low moisture rations (Galyean and Goetsch, 1993; NASEM, 2016).

Eating behavior. Feeding behavior can influence energy intake and expenditure, and thus it is commonly considered when estimating DMI. Susenbeth et al. (1998) reported eating duration (ED) was the best predictor to establish energy intake. Previous studies have reported that feed efficiency is correlated with feeding behavior patterns (Hafla et al., 2013; Cantalapiedra-Hijar et al., 2018; Kelley et al., 2020). In a recent evaluation, Kelley et al. (2020) reported ME intake had the most animal-to-animal variation of all feeding behaviors evaluated. Previously, these eating behavior measurements were too costly to implement commercially.

However, eating behavior is now easily captured using sensors and cameras, which may offer improved predictability for equations determining DMI.

In research settings, feeding behavior is commonly measured using feed monitoring systems that utilize radio frequency identification and gated feed bins (e.g., GrowSafe, Insentec-Roughage Intake Control [RIC] Units-Hokofarm Group, SmartFeed) to record individual animal feed intake in a group pen. Systems wirelessly transfer data on ED and DMI for each individual feeding event to a computer where users can access data files. Previously published studies validating systems using time-lapse video suggest performance of the RIC system is markedly better compared to GrowSafe. Accuracy measured by R^2 for observed and electronically measured bunk visit (BV) frequency was 0.68 and 0.99 for GrowSafe (Mendes et al., 2011) and RIC (Chapinal et al., 2007) systems, respectively. Mendes et al. (2011) reported an R^2 of 0.81 for observed versus measured ED using GrowSafe. GrowSafe units attempt to measure head down duration, or the total time an animal's head is in the bunk by multiplying the number of electronic ID reads by the read rate of the system (Parsons, 2018). Head down eating duration was significantly decreased in low RFI steers (Parsons et al., 2020). However, these relationships should be used judiciously considering the reported accuracy of behavioral measurements using the GrowSafe System.

Previous studies highlight the need to transform BV into meals. Commonly, this is done using a Gaussian-Weibull distribution to depict BV behavior intersecting at the shortest interval between feeding and non-feeding intervals, which can identify a unique meal criterion for each animal based on their eating patterns (Lancaster et al., 2009; Bailey et al., 2012; Parsons, 2018; Kelley et al., 2020). A meal is defined as a series of BV determined by a defined non-feeding interval (i.e., meal criterion). Eating rate, measured as feed consumed per unit of time, is correlated with DMI (Lancaster et al., 2009; Parsons, 2018). More efficient cattle tend to have slower eating rates with a fewer number of BV per day (Montanholi et al., 2009; Kenny et al., 2018; Kelly et al., 2020; Parsons et al., 2020). Heavier cattle tended to be the first to eat and ate longer per day with faster eating rates (Kelly et al., 2020). Cattle that ate at faster rates tended to have shorter feeding events, and cattle with greater total daily ED tended to eat at a slower rate with longer feed events (Kelly et al., 2020). Conversely, Parsons et al. (2020) reported small variation in eating rate and DMI, which would be favorable for DMI prediction. These behavioral differences indicate opportunity for improving DMI prediction equations by accounting for differences in eating behavior.

Prediction models. Tedeschi et al. (2004) identified two broad types of equations used to predict DMI. One type was developed with BW and DMI for a given days on feed, resulting in a curvilinear relationship between DMI and days on feed (Thornton et al., 1985; Hicks et al., 1990). Intake curves depict rapid increase in DMI early in the feeding period, followed by a plateau, and a decline as an animal approaches its harvest BW. The second type is developed using overall BW and DMI feeding period averages and results in a nearly linear relationship between DMI and days on feed (NRC, 2000; McMeniman et al., 2010). The DMI prediction equations based on pen averages can include adjustment factors to account for dietary energy, environmental conditions, and animal maturity (NRC, 2000). These relationships are supported by the notion that as body fat increases, DMI decreases (Fox et al., 1988; Guiroy et al., 2001).

Body weight is a well-known predictor for determining DMI and is commonly included as a scaling factor in DMI equations. For cattle consuming grain-based diets, initial BW has substantial predictive value (NRC, 1987). The popular model developed by Hicks et al. (1990) included initial SBW, days on feed, and mean DMI from d 8 to 28 as predictors. Including mean DMI for the first several weeks in the feedlot as a model predictor significantly improved accuracy (mean $R^2 = 0.85$). This is of practical importance to feedlot producers as they may be able to use a system to measure intake for a short period of time and accurately predict intake and growth for the entire feeding period (Oltjen and Owens, 1987). Additional DMI data estimates improved model predictability; however, estimates of ADG may be able to be used as a proxy for DMI data. An iterative approach was used to predict DMI using dietary energy, BW, and either a known DMI or ADG (Tedeschi et al., 2004). The empirical equations developed by Hicks et al. (1990) are often criticized as they did not adjust for frame size or body fatness, which are known to alter feed intake (Tedeschi et al., 2004; NASEM, 2016).

Perry and Fox (1997) predicted DMI of 192 beef steers varying in breed, but the model only accounted for 48% of the variation in DMI, with a 3% overprediction bias. However, these simple DMI prediction equations were based on NE_m and NE_g determined using NRC (1996) equations, which were subsequently adjusted. McMeniman et al. (2009) applied the NRC (1996) equations and reported significant mean and linear biases when applied to commercial feedlot data. These equations were subsequently revised (McMeniman et al., 2010) and adopted by the NASEM (2016):

Steers: DMI, kg/d = 3.830 + 0.0143 × initial SBW

Heifers: DMI, kg/d = 3.184 + 0.01536 × initial SBW

Initial SBW explained 57 to 76% of the variation in observed DMI. Explained variation improved from 68 to 83% with the addition of mean DMI for d 8 through 28 as a model predictor.

However, these equations fail to account for body composition, which is known to impact DMI (Fox et al., 1988). The Cornell Value Discovery System (Tedeschi et al., 2004), based on growth models by Fox et al. (1992) and Tylutki et al. (1994), simulates growth rate and feed efficiency. The model applies growth equations to predict average expected feed requirement using observed ADG and BW. Many of the intake equations used are static (McMeniman et al., 2010; Anele et al., 2014), so that a single intake value is used for the pen over the entire feeding period. However, since feed intake changes over the course of the feeding period, performance and application of these static equations are limited. A dynamic approach to DMI prediction is needed to accurately predict intake on a daily basis.

A recent dynamic DMI prediction model used feeding behavior measured in the RIC system (Davison et al., 2020). A basic mixed model and two machine learning techniques were applied, but model accuracy was always low ($R^2 < 0.50$). This feed intake model was relatively simple, as it did not classify BV into meals or account for dynamic changes body composition, which have both been consistently shown to affect DMI. Davis et al. (2014) used multiple-regression analysis to determine the relative contribution of initial BW, DMI, feeding behaviors, digestibility, and passage rate to variation in BW gain. When meal events and meal size were substituted for DMI, there was a decrease (30%) in variance accounted for in BW gain. This suggests that eating behavior may not be an important factor for determining BW gain, but further research is needed to determine its effect on DMI. There is considerable opportunity for updating DMI prediction equations using dynamic modelling techniques.

USE OF PRECISION LIVESTOCK TECHNOLOGIES IN FEEDLOT SYSTEMS

Profitability has always been challenging for beef producers, but modern cattle producers and industry leaders are challenged by multifaceted, complex problems. Beef production is under scrutiny for its environmental impact (greenhouse gas emissions, land and water use), animal welfare, and type of production system, but it still must provide wholesome, palatable, affordable beef. However, implementation of PLT in feedlot systems provides substantial opportunity to evaluate sustainability, monitor animal health and welfare, and improve production efficiency and sustainability.

Precision technologies (i.e., cameras, sensors, software) are being applied in beef production systems to help mitigate these complicated production challenges. Precision technologies are often feasible for feedlot producers to adopt, as feedlot systems are intensive confined systems that are typically highly industrialized with respect to feed milling and delivery, cattle processing, and health management (Mendez et al., 2022). Considering the confined nature of feedlots, these Wifi and cellular enabled sensor technologies could be implemented and used to collect high resolution data on feeding behavior, DMI, BW, and body composition, and even methane or CO_2 emissions in cattle. This data can be combined with machine learning algorithms and existing growth models to identify marketing and production optimums.

Machine learning algorithms have been used to predict BW (Cominotte et al., 2019; Miller et al., 2020; MacNeil et al., 2021), hip height (Tadesdemir et al., 2019, Weber et al., 2020), carcass composition (Miller et al., 2020; Matthews et al., 2022); detect heat stress (Chapman et al., 2021); and identify sick or lame cattle (Warner et al., 2022). Deep learning is also a technique effective for evaluating images (Matthews et al., 2020). Deep learning, a subset of machine learning, uses complex algorithm networks to perform a specialized task (Janiesch et al., 2021). Additionally, precision tools for taking images and body measurements chute side have been combined with algorithms to sort cattle into similar groups to reduce carcass discounts (Garcia et al., 2005; Sperber, 2018). This review will focus on the application of PLT and advanced learning algorithms to advance growth and DMI prediction models in feedlot production systems.

Prediction with cameras. There are two methodologies used to estimate BW using precision technologies in feedlot systems. The first involves the use of cameras to record images and apply modeling and learning techniques to evaluate image features and predict BW and composition. Advanced learning techniques such as artificial neural networks (ANN), random forests, dimensionality reduction algorithms, and support vector machines have been shown to predict BW better than traditional approaches such as multiple linear regression and partial least square regression (Cominotte et al., 2019; Miller et al., 2020; Neethirajan, 2020). The second technique uses in-pen, platform scales that may be positioned in an alleyway or in front of water troughs to capture individual full body or front quarter weight when animals are transiting or drinking, respectively. In the case of front quarter BW, weights are combined with proprietary algorithms to predict full BW (MacNeil et al., 2021). Body weight estimation using cameras and scales each have their own advantages and disadvantages.

Cominotte et al. (2019) developed an automated computer vision system using Nellore cattle to predict BW and ADG of growing and finishing beef cattle. Images were taken with 3D cameras and BW and ADG were predicted using ANN. For the feedlot phase, BW and ADG predictions were highly accurate ($R^2 = 0.92$; $R^2 = 0.82$) with a RMSE of 7.7 and 0.9 kg for BW and ADG predictions, respectively. Using the same ANN approach Miller et al. (2020) predicted BW and cold carcass weight. R^2 and RMSE was 0.77 and 37 kg and 0.88 and RMSE = 14 kg for BW and cold carcass weight, respectively.

The use of 2D cameras has also been evaluated, which may offer improved affordability. Gjergji et al. (2020) reported a mean absolute error of 23.2 kg when predicting BW with 2D cameras. In dairy cows using 2D cameras, Weber et al. (2020) achieved an R^2 and RMSE of 0.70 and 42.5 kg, respectively, which was similar to what Miller et al. (2020) reported using 3D imaging in beef cattle. In dairy cows, body measurements were taken with 2D imaging, and BW was predicted with high accuracy ($R^2 = 0.98$; Tadesdemir et al., 2011). Hip height was also investigated using cameras, but results were variable. Tadesdemir et al. (2011) reported an accuracy of 97.9% for estimating HH, but Weber et al. (2020) reported a significantly lower accuracy (55%). The difference could be due to breed effects, but substantially more research needs to be done in this early developing field. On a commercial basis, HH has also been measured in the chute at the time of the initial processing using a height stick mounted chute side to ensure consistent placement of the measuring stick (Garcia et al. 2005; Crawford, 2020).

Matthews et al. (2022) used deep learning techniques to estimate estimated meat yields for specific cuts using carcass 3D images taken directly after harvest. High accuracy (RMSE = 2.8 kg) indicated such technology could be used to predict carcass cut-out. Machine learning has also been used to predict carcass quality and grades using cameras. Miller et. al (2020) predicted fat and conformation grades, which are commonly used in European cattle grading systems. The accuracy was 54.2% for fat grade and 55.1% for conformation grade. However the authors stated, when ultrasound measurements were used for prediction, only slightly more accurate grade estimates were achieved. If such accuracy of models predicting carcass grade could be improved, this would be a highly valuable tool for feedlot producers to establish optimal day of harvest. Although there has been no published research regarding the use of cameras to estimate back fat thickness or body condition score (BCS) in beef cattle, 3D cameras have been used to predict BCS in dairy cows (O'Leary et al., 2020). This suggests that with further research and refinement, cameras could be used to estimate body fat in feedlot animals. The ability to accurately and inexpensively measure body fat would be valuable to producers, by greatly improving growth predictions and determining optimal time of harvest.

Prediction with scales. Considering the relative novelty of the technology, few published studies have evaluated the use of in-pen scales for BW estimation. GrowSafe scales were used to collect partial BW on animals (n = 8,972), and a proprietary algorithm was used to convert partial front quarter BW to full BW (MacNeil et al., 2021). Predicted BW was compared to BW measured using a traditional scale, and BW were accurate with 95 ± 0.9 % of variation in observed BW was explained by partial BW predicted BW. Average daily gain and predicted BW were also strongly correlated (r = 0.95). Similarly, Kolath et al. (2007) also used partial GrowSafe scales for a 62-d trial. Majority of the animals visited four times or less a day, with the number of total visits in the feeding period per animal ranging from 109 to 577 visits. When compared to observed chute weights, partial weights were highly correlated (r = 0.97).

Variation occurs day-to-day with traditional weighing methods due to gut fill. The mean difference between consecutive-day BW was 0.1 ± 8.8 kg, which was recommend as the lower limit of estimation procedures for converting partial BW to predicted BW (Benfield et al., 2017).

Based on analysis of measurements from 7,025 feedlot cattle, Benfield et al. (2017) recommended the equation for predicting full BW using front quarter BW:

$$BW = 1.677 \times \text{front quarter BW}$$

Further research is needed to compare the accuracy of predicted BW derived using the above equation to predict BW estimated using proprietary GrowSafe algorithms. Research studies indicate partial BW can be used to effectively predict full BW. Further comparisons should be made with competing technologies, like SmartScales, to determine differences in underlying algorithms and analyses, which may offer improved predictability. As highlighted by MacNiel et al. (2021), the number of days required to determine accurate ADG using partial BW is of practical importance. It was concluded that a 35-d period with daily weighing was insufficient, but with a 50-d test period, accuracy of ADG prediction was 80%. Manafiazar et al. (2017) stated there are economic benefits associated with a shorter testing period, thus more research is warranted to determine the minimum testing period required. Finally, considerable research must be conducted to determine the upshot of using dynamic BW in growth and DMI prediction models.

Sorting systems. Sorting cattle has been consistently proven to reduce within-pen variation and improve profitability (Smith et al., 1988; Oltjen and Sainz, 1994; Garcia et al., 2005). Historically, cattle have been sorted by BW, as this is an easily attainable chute-side measurement. Smith et al. (1988) reported pens with BW SD of 18 kg had a profit of \$46 ± 0.14, compared to a pen with a BW SD of 72 kg and profitability of \$10 ± 0.77. Hilcher et al. (2005) evaluated several sorting strategies using cattle fed Zilmax. In the first study unsorted controls (CON) were compared to sorting the heaviest 20% and marketing them 28 d earlier than the remainder of the pen. The average DOF for the CON and sorted pens were d 165 and d 173, respectively. Sorting was evaluated on d 0 (EARLY), 100 d (MID) before harvest, and 50 d (LATE) before harvest to determine which was most profitable. Regardless of day of sorting, sorting resulted in heavier final BW compared to CON, but no differences in DMI were reported. Sorted groups had increased HCW, decreased HCW variation, and fewer overweight carcasses. Interestingly, there was no benefit to sorting later, sorting at d 1 resulted in the greatest HCW (Hilcher et al., 2005). This makes this strategy easy to implement, as cattle can just be sorted based on arrival weights, which is typically standard at most feedlots.

In the second study, four treatments were evaluated—1) CON-, 2) CON+, 3) an early weight sort fed Zilmax (1- SORT) where the heaviest 20% were identified upon entry to the feedlot and marketed 14 d before –CON and +CON, with the remaining 80% of the pen fed 7 d longer than controls, and 4) a 4-way sort 50 d from harvest fed Zilmax (4-SORT) with steers sorted into HEAVY, MID-HEAVY, MID-LIGHT, and LIGHT groups, marketed −14, 0, +7, and +28 d from –CON and CON+, respectively (Hilcher et al., 2005). There were no differences in final BW, but average DMI was significantly lower for sorted groups compared to controls. As in experiment one, sorted groups had increased HCW with a decrease in HCW variation and overweight carcasses (Hilcher et al., 2005). With feedlots harvesting hundreds of thousands animals annually, these savings on feed and carcass discounts add up to sizeable increases in profit.

Since cattle reach a specified composition at varying BW, it has been proposed that sorting by DOF estimated using growth models that account for frame and/or body fatness are better than sorting by BW (Sainz and Oltjen, 1994; Sainz et al., 1995; Tedeschi et al., 2003;

Garcia et al., 2005). Sainz and Oltjen (1994) used the DGM to determine DOF using BW, HH, and BF measurements. Unsorted cattle were compared to cattle sorted by BW and DOF, and mean BW, ADG, carcass weight, marbling score, and BF did not differ across groups. However, cattle sorted by DOF were significantly more uniform with decreased pen SD for initial BW, ADG, and adjusted BF, and greater percent low choice carcasses were achieved (Sainz and Oltjen, 1994). In a follow up study, cattle were sorted into short and long DOF groups (Sainz et al., 1995). Cattle were harvested based at an observed BW of 520 kg, which was d 173 and d 205 for short and long cattle, respectively. With sorting, there were no differences in carcass weight, but BF variation was reduced from 47% initially to 10% at slaughter.

The Cattle Classification and Sorting System utilizes BW, HH, and rump measurements that are input in the Cornell Value Discovery System (Tedeschi et al., 2003) to predict a final BW. The current and target finish weights are combined with ration energy and used to project daily feed intake and growth using the growth model. The model predicts expected DOF that is used to identify sort groups, with weight breaks optimized by the system to balance pen counts. Under commercial implementation, cattle were sorted at reimplantation and compared to unsorted controls (Garcia et al., 2005). Sorted cattle had a net value increase of $9.03 per animal and an 18% decrease in HCW variation.

It has been suggested that the optimal sorting strategy should be based on profitability and harvest time should be the day in which feeding an animal one day longer provides no additional return (Oltjen and Owens, 1987; Pyatt et al., 2005). Pyatt et al. (2005) compared sorting by carcass weight, YG, and a BEST endpoint defined by maximum profit using simulations and evaluating profitability harvesting at d 90, 60, and 30 before slaughter to calculate profit over a range of scenarios. Sorting by BEST improved profit per animal by 15%, and sorting by carcass weight and YG yielded similar profit, $186.81 and $185.63, respectively. Moreover, sorting by carcass weight decreased overweight carcasses with no effect on YG, particularly when cattle were overfed. With these retrospective analyses, it was discovered sorting does not need to pinpoint each animal's BEST to result in economic gains; rather, increasing HCW and decreasing discounts improves profit (Pyatt et al., 2005). Similarly, Basarab et al., (1999) reported sorting was effective to improve profit as it identified cattle that could be fed longer to improve QG without YG 4 or overweight carcass risks.

Based on the literature, opportunity exists for utilizing growth models to determine DOF and sort cattle to improve profitability. Previous studies have focused on quantifying the incremental profit increase from sorting by BW or DOF. However, with new emerging technologies and the ability to obtain more frequent BW and accurate DMI trajectories, questions remain about how this new information should be used. It is important to recognize that implementing the BEST strategy would only be able to be implemented at a pen level, as commercial feedlot production requires marketing a pen a whole. However, further research should be conducted to demonstrate the value of sorting using dynamic information obtained from PLT, as well as determining the optimal sorting strategy.

Feeding and bunk management. Day-to-day variation in feeding time and DMI causes digestive upsets and has a negative impact on feed efficiency (Pritchard and Bruns, 2003; Schwartzkopf-Genswein et al., 2003). Considering this, PLT are being used in combination with machine learning techniques to predict feeding behavior and feed disappearance. Deep learning using cow-face images at the feed bunk were used in dairy cows to predict feeding behavior (Kuan et al., 2019). Preliminary results indicated that feeding behavior could be predicted with an accuracy of 78%. Bezen et al. (2020) applied deep learning techniques to evaluate DMI in cows and reported feed consumed per meal ranged from 0 to 8 kg with a MAE of 0.127 kg. However, the authors highlighted the need for additional training with diverse data, as training with homogenous data resulted in significantly greater errors.

Dorea and Cheong (2019) predicted feed disappearance and cattle occupancy at feedlot bunks. Prediction accuracies across bunk score categories were: 81.8% (empty), 82.4% (low), 88.8% (medium), and 90% (full). For cattle behavior, accuracies were: 83.7% (empty), 66.6% (low), 71.4% (medium), and 86.6% (full). Further research should be conducted to refine accuracies at low feed levels, as this is of greatest importance to feedlot producers when determining feed calls in a slick bunk system. In a similar study, feed volume and weight were measured using machine vision and 3D images (Shelley et al., 2016). Results indicated feed volume measurements could be made to within 0.5 kg of feed weight physically measured using a digital scale. However, this study used small RIC feed bins that do not resemble conventional bunk lines. Substantial research is needed to validate these findings and apply algorithms to rations varying in composition and various feed bunks. Nevertheless, these initial findings indicate that precision technologies can be used to evaluate bunk and feeding management.

CONCLUSIONS

Adoption of PLT provide opportunities to collect vast amounts of data to build mechanistic models and advanced heuristic algorithms to evaluate feedlot cattle growth and DMI. These dynamic models can be incorporated into producer support tools to make informed decisions on sorting, ration formulation, feed management, and optimal marketing. Historically, mechanistic modeling has been used to establish scientific knowledge and explain complex patterns; however, as we collect vast amounts of data from sensors, it will be critical to use dynamic, data-driven methods (e.g., artificial intelligence) for data processing. Achieving continued progress in beef production efficiency will require a combination of modelling techniques and precision livestock technologies.

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CHAPTER 2: EVALUATION OF THE DAVIS GROWTH MODEL USING MODERN ANGUS-CROSS CATTLE

INTRODUCTION

Profitability has always been challenging for beef producers, but climate change has led to increased scrutiny of beef cattle production for its environmental impact, and consequently there is substantial interest in improving the economic and environmental sustainability of beef production. With feed costs representing over 70% of total operating costs in feedlot systems (Nielsen et al., 2013), feed efficiency is often targeted as a means of improving biological and economic efficiency. Alternative definitions of feed efficiency exist, but gain to feed ratio (G:F), and residual feed intake (RFI), defined as the difference between observed and expected feed intake, are most frequently used (Kenny et al., 2018). Residual feed intake has been targeted to improve feed efficiency because it is mathematically independent of body weight (BW).

It has been well-established that increases in maintenance energy (NE_m) requirements are related to mature BW (Ferrel and Jenkins, 1985; Birkelo et al., 1991; Lalman, 2007). In the past 30 years, mature cow size rapidly increased from the early 1990s through the mid 2000s, which increased cow maintenance energy requirements (Lalman et al., 2015). Since that time, cow mature BW has stabilized. Similarly, in the past 20 years, yearling BW has increased, but during that same period, yearling hip height (HH) has steadily decreased (Buskirk, 2020). The weight-to-frame ratios of modern cattle have changed significantly, and thus the relationships between mature BW, frame score (FS), and maintenance energy requirements have likely changed. According to Ferrell and Jenkins (1985) up to 65 to 70% of the total energy required for meat production is used for maintenance energy. Therefore, accurate quantification of NE_m requirements is critical for evaluating and advancing beef cattle production efficiency.

This evaluation will focus on updating NE_m requirements using the Davis Growth Model (DGM), a net-energy based, dynamic model used to estimate protein accretion and body composition in beef cattle by simulating total body DNA and protein turnover (Oltjen et al., 1986a,b). The model includes two fundamental parameters: 1) maintenance energy (alpha), where NE_m is defined as alpha × empty $BW^{0.75}$, and 2) a protein synthesis rate constant (K2). Since model development and parametrization in the 1980s, the model has been restructured to account for previous rate of protein accretion and prior nutrition (Oltjen et al., 2014). It is hypothesized that due to changes in mature size maintenance energy and protein synthesis coefficients have increased compared to the estimates reported by Oltjen et al. (1986a). The objective of this research was to 1) evaluate parameters alpha and K2 in DGM using modern, heavier, faster growing cattle, 2) identify traits and characteristics that contribute to variation in alpha, and 3) evaluate alpha using NASEM equations.

MATERIAL AND METHODS

Animals and experimental design. All animals were managed in accordance with a University of California, Davis, Animal Care and Use Protocol (#22179). A single lot of Angus-cross steers (n = 132) estimated to be one year of age were purchased from an online video auction market. Steers were received at the University of California-Davis feedyard, fed grass hay, and allowed to rest 5 d before initial processing. At initial processing (d −1) steers were vaccinated with Inforce 3 (Zoetis Animal Health, Florham Park, NJ), Bovishield Gold One-Shot (Zoetis Animal Health, Florham Park, NJ), and Vision 8 + Somnus (Merck Animal Health, Rahway, NJ); given Dectomax Pour-on parasite treatment (Zoetis Animal Health, Florham Park, NJ); and implanted with Revalor-S (Merck Animal Health, Rahway, NJ). An initial BW, HH, and ultrasound measurement for back fat thickness (BF) and ribeye area (REA) were taken. Ultrasound measurements were taken on the left side between the 12th and 13th ribs with an Ibex Evo (E.I. Medical Imaging, Loveland, CO), according to guidelines of the Beef Improvement Federation (BIF, 2018).

Cattle were stratified by BW and those weighing more than ±2 SD from the mean initial BW were excluded from the experiment. A total of 120 steers were used, with 24 steers assigned to feeding in an individual roughage intake control system (RIC, Insentec, Hokofarm Group B.V., Marknesse, the Netherlands) and 96 steers assigned to feeding in conventional bunks (CON). To select a unform set of steers for the RIC group, 48 steers surrounding the initial median BW (i.e., 24 steers above and 24 steers below) were used as an initial pool of candidates for the RIC group. The 48 steers were stratified by BW and randomly assigned to either RIC or CON group, for 24 steers in each group. The 24 steers assigned to the CON were recombined with the additional CON steers. This technique ensured similar initial mean shrunk body weight (SBW) for the 24 RIC steers and 96 CON steers (initial SBW = 346 and 345 kg, respectively). Steers in the RIC group were randomly assigned to one of three pens (i.e., 8 steers/pen), and each steer was assigned its own unique feed bin. The 96 CON steers were randomly assigned to one of eight pens with twelve steers in each pen. All steers were placed in their respective pens on d 0, and RIC steers were given an Allflex (Irving, TX) RFID ear tag.

Steers in the RIC system were gradually trained to use the gated feed bins over a 10-d period. The gates that allowed access to the feed bin were always open, and steers could access any feed bin. After gaining familiarity, steers were each assigned unique feed bins, and the gates were activated, so feed access was only given if a specific RFID was scanned. Individual steer DMI data were collected using RFID ear tag data, including bunk visit start and stop times, the length of the visit in seconds, and kilograms of feed consumed. These records were wirelessly transferred to a local computer where data files were available for download.

Steers were managed and transitioned following the same schedule: starting ration for 31 d, transitioning ration for 14 d, and finishing ration for a minimum of 84 d before harvest (Fig. 2.1). For each new batch of total mixed ration, a representative sample was collected and used to calculate dry matter (DM). Dry matter was calculated as the retained weight after drying in a forced air oven for 36 h at 60°C. Composition by ration type is shown in Table 2.1. Ration NE_m and net energy for gain (NE_g) were calculated using tabular values from NASEM (2016). All cattle were fed twice daily (0630 and 1430), and RIC steers were fed at 10% greater than the previous days intake to ensure *ab libitum* feed access. The CON steers were managed to a slick bunk (i.e., the amount of feed offered closely matches maximal feed intake of the cattle resulting in a 'slick' or empty feed bunk just before the next feeding time) to reflect management practices commonly used in commercial feedlot systems. Daily DMI was recorded on an individual- and pen-basis for RIC and CON groups, respectively. Body weights, HH, and ultrasound measurements were taken every 28 d before morning feeding, and final measurements were taken the day before shipping for harvest.

Cattle were marketed in three groups when they were deemed market ready by means of visual appraisal with consideration of pen mean BW and BF (Fig. 2.1). Based on industry averages for similar frame-sized cattle, a mean pen BW of 634 kg was targeted for heavy body weight pens and 612 kg was targeted for all other pens. Back fat thickness target was 1.1 cm for all groups. Cattle were harvested at a commercial abattoir (Cargill Meat Solutions, Fresno, CA). At harvest, hot carcass weight (HCW) and USDA quality grade (QG) were recorded. Marbling score (MA) was measured by a trained evaluator following USDA (2019) guidelines. Carcass BF and REA were measured. All carcass measurements and evaluation were performed on the left carcass side. Yield grade (YG) was not scored by the plant, so it was calculated using the equation shown in Table 2.2.

Data management. Observed BW measurements were reduced by 4% to determine shrunk body weight (SBW). To reduce variation in weighing and measurement conditions, SBW, HH, BF, and REA were estimated using the slopes of the regression of 28-d measurements for each variable versus time. Estimates for empty body fat (EBF) were calculated using the regressed BF and REA values and used to estimate body composition and energy use using equations listed in Table 2.2. Average daily gain (ADG) was calculated as the slope of the SBW regression. Residual feed intake (RFI) was defined as the residual of the regression of DMI on mid-test $SBW^{0.75}$ and ADG. Gain to feed ratio (G:F) was calculated individually for RIC steers and on a pen-basis for CON steers. To determine SBW and composition for the day cattle began the finishing ration, backward projections (d −12) were made using the slope of the regression for each variable as the 28-d BW, HH, and ultrasound measures were made 12 days after transition to the finishing diet.

Alpha and K2 in the DGM were calculated using data from the finishing ration. The solver function in Excel was used to estimate parameter values for alpha and K2 individually for each RIC steer and on a pen-basis for the CON groups. Values required for parameter estimation were initial SBW, FS, initial EBF percent, final EBF in kilograms, average DMI, DOF, and ration NE_m and NE_g. Frame score was calculated as described by the Beef Improvement Federation (BIF) using the equation shown in Table 2.2. For the DGM frame score scale ranged from 1 to 3, where 1 was a BIF score 2, 2 was a BIF score 5, and 3 was a BIF score 8. To determine the sensitivity of alpha and K2 to initial model values, all values (i.e., ration energy, initial SBW, initial EBF percent, DMI, final EBW, and final EBF in kilograms) were changed ±10% from the observed value. For comparison, alpha values were calculated following the NASEM (2016) equation shown in Table 2.2.

Statistical analysis. All data analysis and graphic visualization were performed in R (version 4.2.1). Graphs were generated using the ggplot2 package. For comparison of RIC and CON cattle, pen means and SD for the eight CON pens were averaged. Normality of variables was assessed using a Shapiro-Wilks test from the base R package. Due to unequal sample sizes and an assumed unequal variance due to the method used to select the RIC subset, effect sizes were computed as described by Cohen (1988) to compare the magnitudes of differences between groups. Pearson correlation coefficients were calculated in the base package of R to evaluate the relationship between alpha, K2, and various production parameters. To describe variation in alpha, linear regression was performed using the *lm* function from the base R package. Alpha regression analysis was only performed using RIC cattle, with individual animal as the experimental unit. Repeated measures (e.g., SBW) were averaged into one value per individual. Model selection was performed using backwards stepwise regression with adjusted R^2, Akaike Information Criterion (AIC), and root mean square error (RMSE) used to determine the best model. Significance was declared at $P < 0.05$.

RESULTS AND DISCUSSION

Performance. Means and SD describing performance of RIC and CON cattle are summarized in Table 2.3. By design, the variation in initial mean BW was numerically reduced for the RIC cattle, as the RIC cattle were specifically selected to be a uniform subset. However, mean initial BW (effect size = 0.21) and final BW (effect size = 0.18) were the same for both groups. Hip height and FS were slightly increased for CON steers. Dry matter intake was decreased in the CON cattle by 6.9% (effect size = 1.00). The decrease in DMI among CON steer was attributed to slick bunk management. It has been well documented in the literature that limit feeding, which has evolved into slick bunk management, has been consistently shown to improve feed efficiency in comparison to *ad libitum* feeding (Galyean et al., 1999; Schwartzkopf-Genswein et al., 2011; Owens and Hicks, 2019). Increased intake for the RIC cattle likely contributed to the numerical increase in ADG (effect size = 0.42), but variation in ADG was the same between groups. There was no difference in G:F (effect size = 0.09). Despite differences in feed intake, performance was relatively similar between RIC and CON groups.

Carcass summary statistics for RIC and CON groups are shown in Table 2.4. All carcasses graded USDA choice or greater. The greatest difference between the CON and RIC groups was in BF (effect size = 0.81), which may have been to differences in bunk management. Increased DMI of the RIC cattle, resulted in increased energy intake, which has been shown to increase carcass BF (Schumacher et al., 2022). Greater BF in the RIC cattle contributed to a numerical increase in RIC group YG. Despite differences in BF, the magnitude of difference in marbling score was very small (effect size = 0.13). Such results are consistent with Brethour (2004), who reported low correlations between marbling score and BF. All other carcass attributes were similar between groups (Table 2.4).

Initial results. Based on analysis on the RIC steers, mean alpha (i.e., maintenance coefficient) was 0.09676 with a SD of 0.0149. A distribution of alpha values for RIC steers is shown in Fig. 2.2a. A slight positive skew was observed in the histogram, but the data was determined to be normally distributed based on a Shapiro-Wilks test (P = 0.11). Mean (±SD) K2 for RIC steers was 0.048226 ± 0.0029, and the distribution of K2 values was normal (P = 0.47; Fig. 2.2b). Results from the current study suggest a 15.1% increase in maintenance energy and an 8.6% increase from the K2 from the previous estimates reported by Oltjen et al. (2014). Compared to the original estimates for alpha and K2 by Oltjen et al. (1986a), Oltjen et al. (2014) reported a decrease of 2.0 and 3.7% in alpha and K2, respectively. However, changes in parameter estimates by Oltjen et al. (2014) were due to an updating equation for estimating initial DNA, so the same data were used in the analysis. The modern Angus-cross steers used in the current study reflect genetic selection over the past several decades for increased size and growth via emphasis on feed conversion rate and ADG (Crews, 2005; Terry et al., 2020). Therefore, increases in alpha and K2 seem plausible, since genetic selection might be expected to increase maintenance energy requirements and to a lesser extent, protein accretion. The relationship between alpha and K2 is shown in Fig. 2.3. There was little relationship between alpha and K2 (r = −0.19; P = 0.38), which was similar to the correlation reported by Oltjen et al. (1986a).

These parameter estimates assume all initial values are known (and correct). As with many commercial feedlot cattle, the exact age of cattle in the current study was unknown, which contributes to uncertainty in FS calculated using BIF equations, where FS is based on HH at a given age (Cundiff et al., 2010). The Beef Improvement Federation (2018) cautions against current use of FS stating, "predictions of mature BW and carcass weights based on FS are likely incorrect." Equations used to relate FS to mature BW were based on bulls in the 1980s, but since that time, weight-to-frame relationships have drastically changed. Based on Angus Herd Improvement records, a yearling Angus bull with a FS of 5.5 weighs over 68 kg more than a bull in the 1980s with the same FS (Buskirk, 2020). Therefore, FS calculations should be reconsidered, or current FS should be adjusted to increase mature BW.

Frame correction. As an alternative way of estimating FS, a FS adjustment factor was developed using the reference SBW for a steer at 28.6% EBF (478 kg) and observed SBW at 28.6% EBF (Guiroy et al., 2001; NASEM, 2016). A scatterplot of percent EBF and SBW is shown in Fig. 2.4 (R^2 = 0.69). For each individual steer, a simple linear regression and a second order polynomial regression were fit using percent EBF measurements. Based on the criterion of R^2, the polynomial fit was preferred and used in the analysis. A *for loop* in R (version 4.2.1) was used to individually fit polynomial regressions and predict SBW at 28.6% EBF for each steer. Predicted SBW was divided by the reference SBW to calculate an adjustment factor to correct FS based on percent EBF. For percent EBF adjusted FS mean (± SD) was 7.2 ± 1.32, and the previous BIF calculated FS was 6.7 ± 0.65. There was no relationship (r = −0.01) between the percent EBF corrected FS and previous BIF frame score (Fig. 2.5). Some FS were outside of the normal expected range (i.e., 5 to 7), but there were no systematic errors when percent EBF corrected frame scores were plotted against SBW at 28.6% EBF (Fig. 2.6). These new percent EBF corrected FS were used to determine final estimates of alpha and K2.

Parameter estimates. Means and SD for alpha are shown in Table 2.5. Alpha ranged from 0.0752 to 0.1307 with a mean and SD of 0.0901 and 0.0150 using EBF percent adjusted FS. The distributions of alpha and K2 using EBF percent adjusted FS are shown in Figures 2.2c and 2.2d, respectively. Compared to the previous alpha estimate using standard BIF frame scores, there were no differences in alpha (P = 0.89) or K2 (P = 0.56). Although mean alpha was nearly the same, individual animal values were more variable, and the relationship between alpha and K2 intensified. There was a tendency (P = 0.06) for alpha to lessen with greater K2 (r = −0.38). In both Oltjen et al. (1986a) and the previous evaluation of alpha and K2 using BIF frame scores, an inverse relationship between alpha and K2 was detected, but it was not significant. An analysis that was conducted using a data set from Dykier (2017) with BIF frame scores, showed the negative relationship between alpha and K2 was significant (r = −0.26; P = 0.05). These results suggest greater maintenance energy requirements are associated with lower rates of protein synthesis

There were no differences in alpha based on harvest date (P = 0.53). Alpha and K2 were decreased in the CON cattle by 9.0 and 7.4%, respectively. The smaller alpha observed in the CON group may be due to bunk management. Greater efficiency with slick bunk management is in part due to altered animal energetics (Owens and Hicks, 2019). Andreini et al. (2020) fed cattle *ad libitum* to determine RFI classification, and subsequently cattle were feed restricted. There were no differences in maintenance energy requirements among RFI groups when cattle were fed *ad libitum*, but under feed restriction NE_m decreased for both groups, but decreases in NE_m were greater in low RFI steers. As such, the decrease in alpha among the CON steers could be due to the slight limiting of feed intake from slick bunk management. The range in alpha values reported in the present study was consistent with those previously reported: 0.081 to 0.135 (Oltjen at al., 1986a; Zinn, 1988; Andreini et al., 2020). Results from the current study and the literature indicate alpha is highly variable. Further, all these estimates assume alpha is static throughout the feeding period, but it almost assuredly changes over the course of the feeding period.

Table 2.6 shows Pearson correlations for alpha and K2 with various production parameters based on data from the RIC steers. Alpha decreased with greater EBW ($r = -0.49$; $P = 0.02$), and K2 and EBW had a strong positive correlation ($r = 0.47$; $P = 0.02$). The relationship between alpha and EBW is surprising, given increases in cow size have been consistently shown to increase NE_m requirements (Ferrell and Jenkins, 1985; Lalman, 2007). As expected, the correlation between K2 and EBW was positive, suggesting heavier steers grew faster. The inverse relationship between alpha and EBW could be due to the small sample size and that the heavier steers were simply more efficient. The relationships between alpha, K2, BIF frame score, and HH were low ($r < 0.10$), suggesting growth and energy requirements have little relationship to HH. But percent EBF corrected FS was strongly correlated with K2 ($r = -0.47$), indicating while FS might not be critical for estimating alpha, it is important for determination of K2. Therefore, FS calculations should be reconsidered, or current FS should be adjusted to increase mature BW.

Alpha was negatively correlated with DMI ($r = -0.20$), supporting the theory that energy intake is controlled by more than just energy requirements, but rather controlled by a multitude of complex mechanisms and factors, including endocrine signaling, physiological cues, metabolism, and feeding behavior (Allen, 2014). The positive correlation ($r = 0.26$)

between K2 and DMI suggests animals that grew faster ate more. Similarly, Van Koevering et al. (1995) reported greater ADG was associated with increased DMI. In the current study, ADG was strongly correlated ($P < 0.001$) with smaller alpha and greater K2, indicating faster growing steers had greater protein synthesis demands, but were also more efficient with lower maintenance energy requirements. Kelley et al. (2010) calculated relative growth rate (RGR) and reported a significant correlation between ADG and RGR, which was similar to results of the current study, but a non-significant relationship was reported for DMI and RGR. As expected with efficiency measures, RFI ($r = 0.47$) and G:F ($r = -0.80$), were highly correlated with alpha. With greater RFI, K2 tended ($P < 0.10$) to decrease, and G:F significantly increased with increased K2 ($r = 0.73$). Protein synthesis was greatest in efficient steers. Kelley et al. (2010) reported no relationship between RFI and RGR, but consistent with the current study, highly significant correlations were reported for ADG, RGR, and G:F. In progeny from bulls selected for high and low maintenance energy requirements, no relationship was reported between maintenance energy and RFI (Welch et al., 2012). However, this study did not estimate maintenance energy requirements or alpha on a per animal basis, so there no way to correlate individual steer maintenance with RFI like in the current study.

Ribeye area was negatively correlated with both alpha and K2, but relationships were small and non-significant (Table 2.6). In the literature, low correlations between RFI and REA have been reported (Cruz et al., 2010; Santana et al., 2012), which would suggest maintenance requirements are also weakly correlated with REA. Back fat thickness tended ($P = 0.06$) to increase with decreasing alpha, but there was no correlation with K2 ($r = 0.04$). Percent EBF and alpha were also negatively correlated ($r = -0.29$), but K2 and percent EBF were strongly correlated (r = 0.54; P = 0.007). This implies that faster growing animals also tended to deposit fat more rapidly. This disagrees with a study comparing RFI in Nellore cattle by Gomes et al. (2010), where it was reported cattle with decreased maintenance requirements had decreased body fatness. The strong relationship between K2 and percent EBF helps explain the interrelatedness of percent EBF corrected FS and K2.

Sensitivity analysis. Table 2.7 shows the percent change in alpha and K2 from adjusting input parameters ± 10% from the observed value. Alpha was most sensitive to initial SBW, resulting in a 28 and −29% percent change for an increase and decrease in observed initial SBW, respectively. K2 was less sensitive than alpha to changes in initial SBW, with increases and decreases changing K2 in the same direction by 10%. For accurate SBW, the shrink factor should be adjusted according to ration type, as Phillips et al. (2006) suggested rumen fill was greater on forage-based diets. It was unsurprising since in initial SBW was strongly correlated with final EBW (r = 0.62), that alpha and K2 were also sensitive to changes in final EBW. A 10% increase and decrease in final EBW changed K2 by 28 and −27%, respectively. Alpha was less sensitive than K2 to changes in final EBW, but interestingly the direction of the change was different—an increase in final EBW decreased alpha by 15%, and a decrease in final EBW increased alpha by 18%. While this may seem counterintuitive, these results are consistent with the correlation coefficients that were presented in Table 2.6. With respect to a producer using this model, capturing accurate individual BW on arrival, and choosing the correct final target BW will be important to accurately predict growth and energy requirements.

Alpha was also highly sensitive to changes in final EBF in kilograms, changing 25% in each direction with 10% increases and decreases in final EBF. Empty body fat was calculated using EBW, BF, and REA measurements, so correct measurements are critical to quantifying alpha. Similarly, with initial percent EBF, which was calculated using EBW, 10% increases and decreases in initial percent EBF resulted in a 19% increase and 18% decrease in alpha, respectively. Based on this, accurate quantification of initial body fatness is nearly equally important as initial BW, but this creates greater challenges for implementation on a large scale. Currently, accurately estimating body fatness requires a skilled ultrasound technician. However, new research using 3-D cameras has investigated predicting body fatness and QG (Miller et al., 2019; Cominotte et al., 2020), and prediction of percent EBF may soon be feasible with computer vision technology.

Contrary to what was expected, FS was not a major contributor to variability in alpha estimates, only changing alpha 1% in same direction for a 10% increase and decrease in the input value. This suggests percent EBF adjusted FS may not be important for quantifying alpha. However, K2 was highly correlated with FS ($P < 0.001$; Table 2.6). Ten percent increases and decreases in percent EBF adjusted FS only changed K2 by 3%, suggesting further analysis is needed. Given the uncertainty in quantifying ration energy, changes to ration NE_m and NE_g were also evaluated. Alpha was more sensitive to NE_g, with 10% increases and decreases changing alpha by 13 and −16%, respectively. Ten percent increases and decreases in NE_m changed alpha by 10 and −5%. K2 was not sensitive to changes in ration energy. This indicates that using tabular methods to calculate is sufficient for growth models, as changes in ration in energy had smalls effects on alpha and K2. Finally, alpha was very sensitive to changes in DMI, changing alpha 24% in the same direction as a 10% increase and decrease in observed DMI. This is of practical importance because measuring individual DMI is typically not possible in commercial feedlot systems but using pen DMI averages will contribute to uncertainty in growth predictions. Further research is needed to determine the effects of estimating alpha using observed and predicted DMI.

Alpha regression. For ease of regression interpretation, alpha was transformed by multiplying the observed alpha by 100. A single observation was determined an outlier, as it was over two SD from mean alpha, and consequently it was removed from the analysis. The final model selected included an intercept and the following predictors: RFI, DMI, SBW, and BF. Adjusted R^2 was 0.78, and the model was significant ($P < 0.001$). Coefficient estimates and SE are shown in Table 2.8. Model RMSE was 0.54, and no mean or slope bias were present. Feeding behavior was available from the RIC system, and the following feeding behavior predictors were included in the model: total daily bunk visit (BV) duration, mean BV duration, BV frequency, mean meal duration, and meal frequency. Feeding behavior was not an important predictor of alpha. While the inclusion of mean BV duration did improve adjusted R^2, prediction errors were increased. In an investigation using regression analysis, Davis et al. (2014) reported meal frequency and duration were not advantageous in predicting BW gain. However, in the current study considering the small sample size (n = 23), further analysis is needed to determine the effects of feeding behavior on maintenance energy requirements.

NASEM Equations. Mean and SD alpha estimated using the NASEM (2016) equation were 0.08013 ± 0.01333. The NASEM equation underpredicted alpha by 18 and 15% for the RIC and CON groups, respectively (Table 2.9). Performance of NASEM equations were slightly better using pen averages. It has been reported the NASEM (2016) equations overpredict the efficiency of converting ME into gain by 20.5% (Cabezas-Garcia et al., 2021), which causes an underprediction of maintenance energy requirements. Further, Tedeschi (2019) reported low correlations between retained energy and retained protein using NASEM (2016) equations, which indicated a relatedness between RP and RE that impacts the ability to accurately predict RE with greater precision. The potential of an erroneous NASEM (2016) equation warrants further investigation, as this could have negative impacts on growth prediction, determination of energy requirements, and ration formulation.

IMPLICATIONS AND CONCLUSIONS

Results from this study indicate an increase in apparent maintenance energy requirements and protein synthesis in modern Angus-cross steers as compared to the historical cattle populations used determine feeding standards. Cattle with decreased maintenance energy requirements tended to be faster growing with increased rates of protein synthesis, but also increased EBF percent. Considering the high correlation between K2 and FS, it will be important to further quantify the relationship between FS, mature BW, and percent EBF. In the context of the DGM, relationships between growth characteristics and DNA max, a proxy for mature BW, have also likely changed. There is a great need to update comparative slaughter trials to determine the relationship between mature BW, FS, percent EBF, and QG. Although relationships between feeding behavior and maintenance energy were unclear in the present study, trends suggest a possible association. Future studies should attempt to answer the effect of feeding behavior on maintenance energy requirements.

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FIGURES

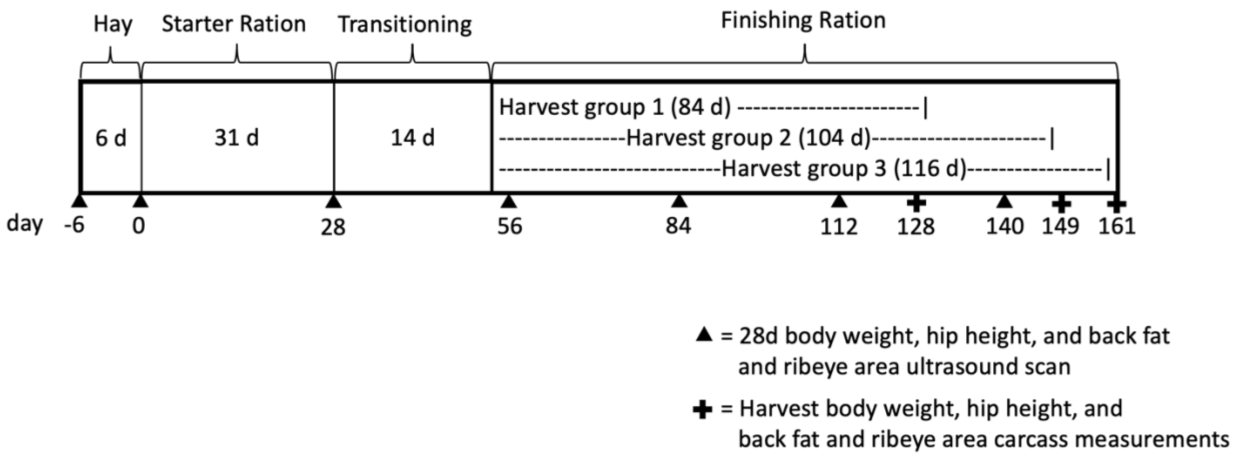

Figure 2.1. Project timeline

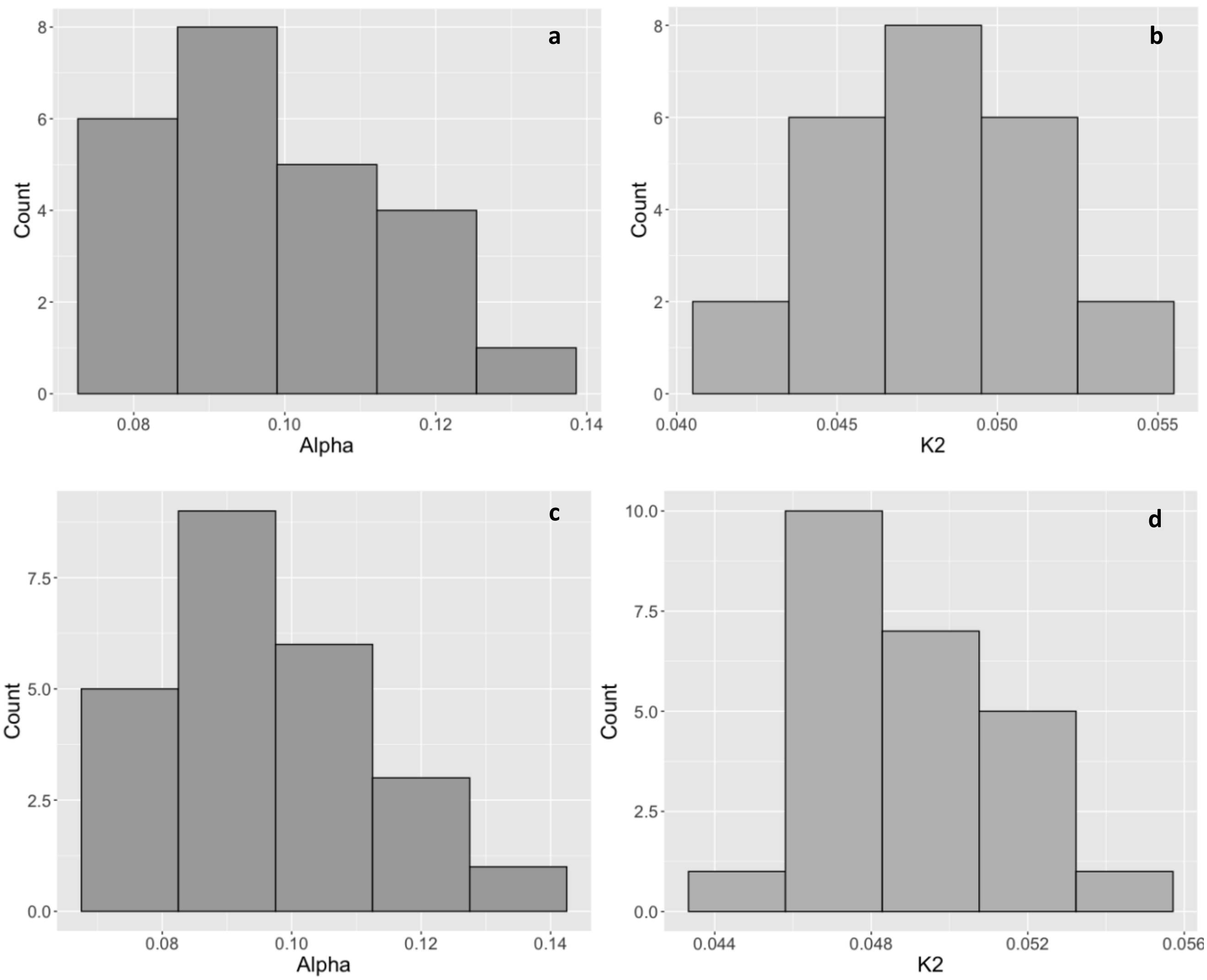

Figure 2.2. Histogram of alpha (NE_m coefficient) and K2 (protein synthesis rate constant) parameter estimates determined using the Davis Growth Model and frames score determined using the Beef Improvement Federation (BIF) equation and empty body fat percent adjustment **a**) Alpha with BIF frame score, **b**) K2 with BIF frame score, **c**) Alpha with percent EBF corrected frame score, and **d**) K2 with percent EBF corrected frame score

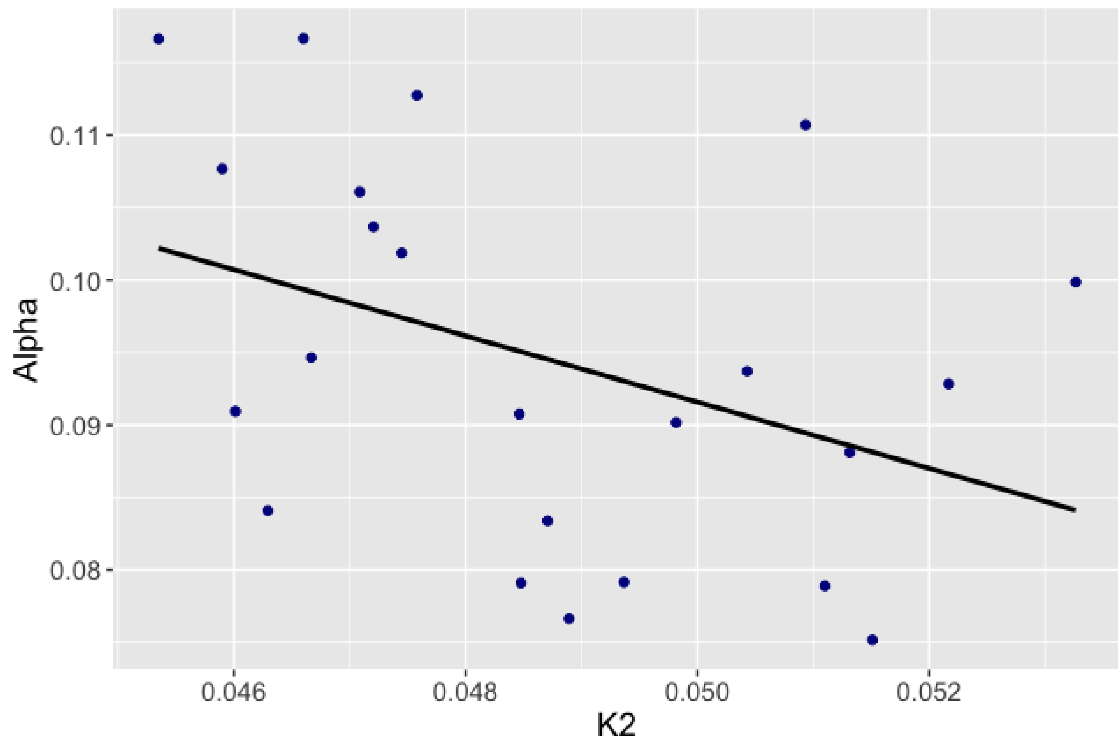

Figure 2.3. Scatterplot of K2 and alpha estimates determined using the Davis Growth Model for steers fed a high concentrate diet individually in a roughage intake control system (RIC) and conventional feed bunks (CON)

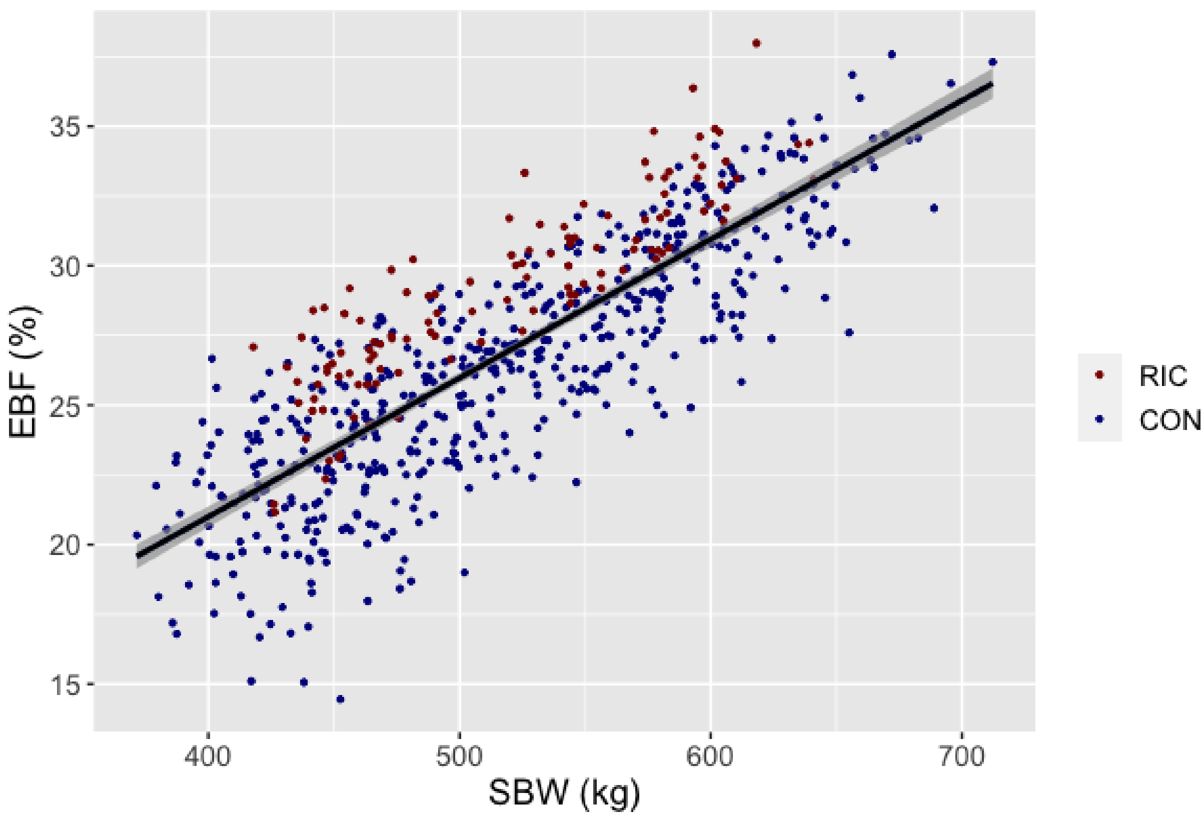

Figure 2.4. Scatterplot of final shrunk body weight (SBW) versus empty body fat (EBF) percent for steers fed a high concentrate diet individually in a roughage intake control system (RIC) and conventional feed bunks (CON)

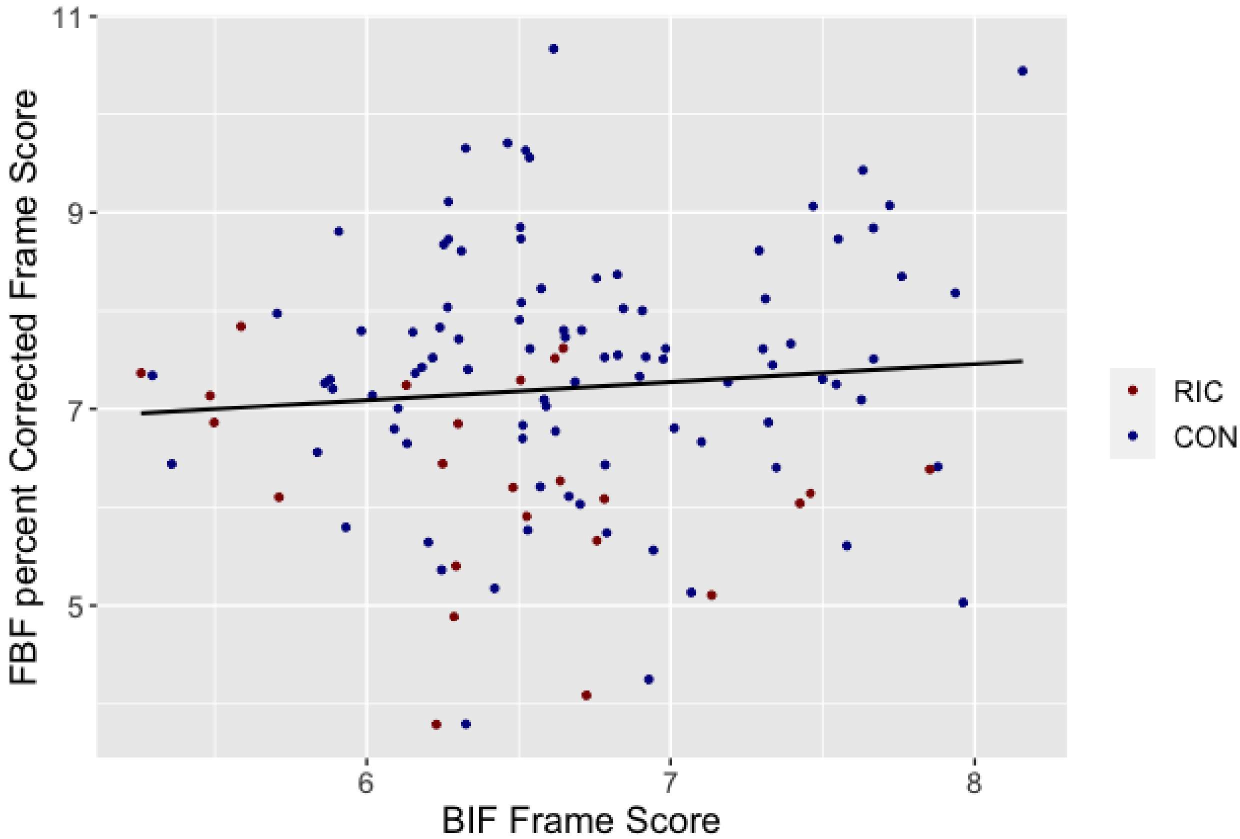

Figure 2.5. Scatterplot of Beef Improvement Federation (BIF) frame scores versus empty body fat (EBF) percent adjusted frame score for steers fed a high concentrate diet individually in a roughage intake control system (RIC) and conventional feed bunks (CON)

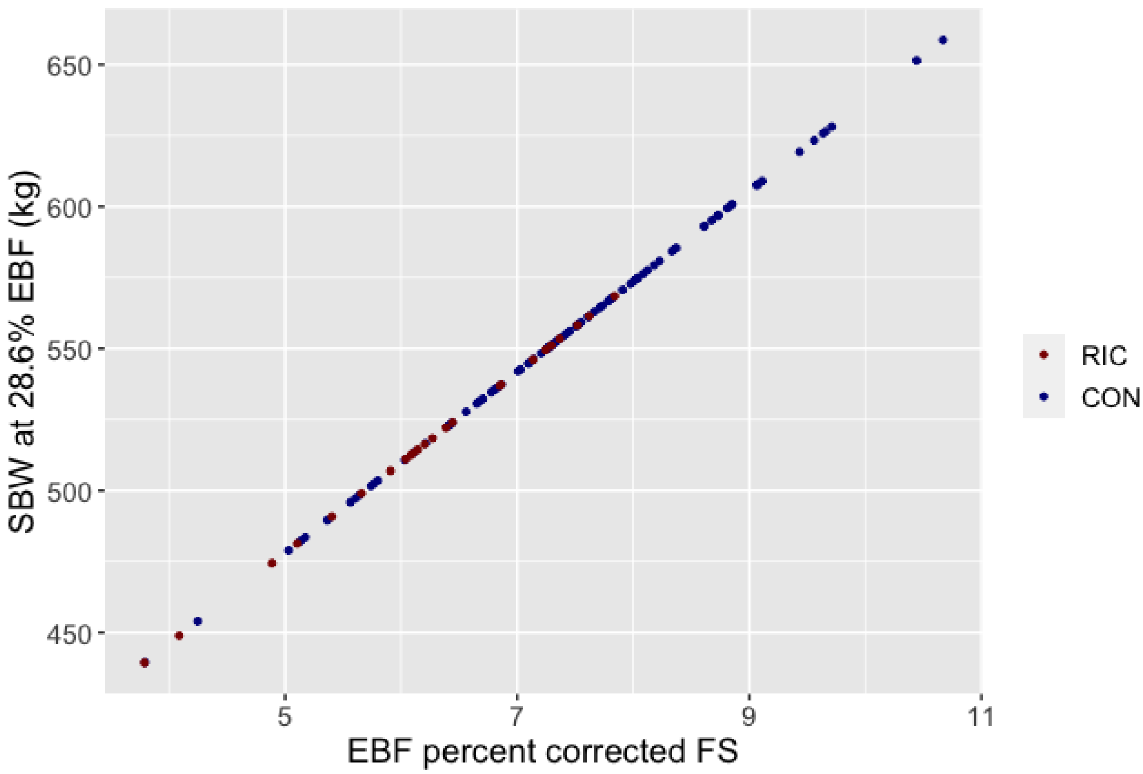

Figure 2.6. Scatterplot of empty body (EBF) percent adjusted frame score (FS) versus shrunk body weight (SBW) at 28.6% EBF for steers fed a high concentrate diet individually in a roughage intake control system (RIC) and conventional feed bunks (CON)

TABLES

Table 2.1. Ration composition on a percent *dry matter basis*

Parameter	Starter	Transitioning	Finisher
Rolled Corn, %	41.99	51.12	72.00
Dried distillers grains, %	20.00	20.00	6.00
Wheat hay, %	15.00	8.00	6.00
Alfalfa hay, %	12.00	10.00	5.00
Yellow grease, %	1.50	2.00	3.00
Molasses, %	8.00	7.00	3.00
Urea, %	0.35	0.40	1.80
Beef trace salt, %	0.32	0.32	1.00
Rumensin, %	0.02	0.02	0.02
Calcium carbonate, %	0.82	1.15	1.80
Magnesium oxide, %	0.32	0.00	0.02
Potassium chloride, %	0.00	0.00	0.50
Ration energy, Mcal/ kg DM			
Maintenance net energy	1.88	1.98	2.02
Gain net energy	1.24	1.33	1.38

Table 2.2. Equations used to estimate body composition, frame score, and energy use

Terms	Equations	Literature Cited
Metabolic body weight, kg	$MBW = SBW^{0.75}$	Kleiber (1947)
Empty body weight, kg	$EBW = 0.917 * SBW - 11.39$	Owens et al. (1995)
Frame Size	$FS = -11.548+(0.4878 * HH/2.54) -(0.0289 * AGE) + (0.00001947 * AGE^2) + 0.0000334 * HH * AGE$	Cundiff et al. (2010)
Yield Grade	$YG = 2.50 + 0.98425*BF + 0.20*KPH + 0.0008379*HCW - 0.0496*REA$	USDA (2019)
Empty body fat, kg	$EBF = (0.351*EBW) + (21.6*YG) -80.8$	Perry and Fox (1997)
Empty body protein, kg	$EBP = (EBW - EBF) * 0.2201$	Garrett and Hinman (1969)
Retained energy, Mcal	$RE = EBF * 9.367 + EBP * 5.686$	NASEM (2016)
Net energy for maintenance intake, Mcal/kg dry matter	$NE_m = DMI-[(RE/kg) / ME \cdot kg\ DM)] * NE_m \cdot kg\ DM$	NASEM (2016)
Alpha	$Alpha = (1.37*ME - 0.138*ME^2 + 0.0105* ME^3 - 1.12) * (DMI - beta* SBW^{0.75}* ADG^{1.097}/(1.42*ME - 0.174* ME^2 + 0.0122* ME^3 - 1.65))/SBW^{0.75}$	NASEM (2016)

Table 2.3. Means and SD for performance traits of steers fed a high concentrate diet individually in a roughage intake control system (RIC) and conventional feed bunks (CON)

Parameter	RIC		CON		Effect size
	Mean	SD	Mean	SD	
Initial body weight, kg	438	12	434	26	0.21
Final body weight, kg	598	26	604	40	0.18
Mean body weight$^{0.75}$, kg	106.3	2.6	108.5	5.1	0.57
Average hip height, cm	131.3	3.13	132.4	2.73	0.38
Frame Score	6.5	0.6	6.8	0.6	0.49
Dry matter intake, kg/d	11.6	0.9	10.8	0.7	1.00
Average daily gain, kg/d	1.92	0.26	1.81	0.26	0.42
Gain:Feed	0.166	0.02	0.167	0.01	0.09
Final empty body fat, %	32.2	2.16	31.1	2.60	0.46
Residual feed intake, kg/d	0.00	0.52	-	-	-

Table 2.4. Means and SD for carcass traits of steers fed individually in a roughage intake control system (RIC) and conventional feed bunks (CON)

Parameter	RIC		CON		Effect size
	Mean	SD	Mean	SD	
Hot carcass weight, kg	367	20	374	26	0.30
Dressing, %	62.1	1.26	62.5	1.41	0.31
Yield Grade	3.5	0.50	3.2	0.65	0.52
Back fat thickness, cm	1.6	0.32	1.3	0.41	0.81
Ribeye area, sq cm	88.3	5.62	90.75	8.35	0.35
Marbling score[1]	576	78.9	564	95.6	0.13
USDA Quality Grade Prime, %	8.3	-	9.4	-	-

[1]Marbling score (slight^{00} = 300, small^{00} = 400, modest^{00} = 500, etc.)

Table 2.5. Alpha and K2 fit using the Davis Growth Model and empty body fat adjusted frame size for steers fed individually in a roughage intake control system (RIC) and conventional feed bunks (CON)

Parameter	RIC		CON		Effect size
	Mean	SD	Mean	SD	
Alpha	0.09617	0.01512	0.08755	0.01556	0.56
K2	0.04866	0.00222	0.04505	0.00340	1.14

Table 2.6. Pearson correlation coefficients for alpha and K2 associated with different mean production parameters based on steers fed individually in a roughage intake control system

Parameter	Alpha	K2
Empty body weight	−0.49[a]	0.47[a]
BIF frame score[1]	−0.06	0.06
EBF adjusted frame score[2]	0.04	0.47[b]
Hip height	−0.06	0.07
Average daily gain	−0.65[b]	0.62[b]
Residual feed intake	0.47[a]	−0.40
Dry matter intake	−0.24	0.26
Gain:Feed	−0.80[b]	0.73[b]
Ribeye area	−0.23	−0.07
Back fat thickness	−0.39	0.04
Empty body fat percent	−0.29	0.54[b]

[1] Beef Improvement Federation Calculated frame score (Cundiff et al., 2010)

[2] Empty body fat percent adjusted frame score

[a] $P < 0.05$

[b] $P < 0.01$

Table 2.7. Changes in parameter estimates for alpha and K2 from adjusting model input values ±10% in the Davis Growth Model

Parameter	Alpha[1]		K2[2]	
	+10%	−10%	+10%	−10%
DMI, kg	24.10	−24.11	−2.31	3.04
Frame Score (EBF% adjusted)	1.10	−1.21	−3.18	3.37
Initial SBW, kg	27.93	−29.29	−10.13	10.79
Initial EBF, %	18.57	−18.22	2.35	−2.26
Final EBW, kg	-15.00	18.39	28.44	−27.33
Final EBF, kg	−25.44	25.97	−9.96	9.58
Ration NE_m, Mcal/kg	9.94	−5.97	−1.01	0.65
Ration NE_g, Mcal/kg	13.00	−15.96	−0.79	0.77

[1] Baseline: 0.09604

[2] Baseline: 0.04817

Table 2.8. Regressions coefficients and error estimates for alpha predicted using a linear regression model[1]

Parameter	Estimate	Standard error	P-value
Intercept	8.68	5.08	0.10
Residual feed intake	3.08	0.42	<0.001
Dry matter intake	−1.50	0.33	<0.001
Shrunk body weight	0.05	0.02	0.01
Back fat thickness	−3.76	0.96	0.001

[1]Alpha transformed by multiplying by 100 for ease of interpretation

Table 2.9. Alpha fit using empty body fat adjusted frame size for steers fed individually in a roughage intake control system (RIC) and conventional feed bunks (CON)

Parameter	RIC		CON		Effect size
	Mean	SD	Mean	SD	
Alpha	0.0815	0.0141	0.0760	0.0106	0.45

CHAPTER 3: EVALUATION OF CATTLE FEEDING BEHAVIOR MEASURED IN INDIVIDUAL FEED BINS AND CONVENTIONAL BUNKS

INTRODUCTION

Dry matter intake (DMI) monitoring is important for evaluating animal health, feed efficiency, and profitability. However, accurate DMI monitoring is not widely used in commercial feedlots due to existing infrastructures and the high costs associated with obtaining such measurements. Historically, measuring DMI has been a time and labor-intensive process requiring direct animal observation, time-lapse video recording, and manual measuring of feed offered and refusals (Chizzotti et al., 2015). Schwartzkopf-Genswein et al. (1999, 2002) monitored bunk attendance using radio frequency identification (RFID) ear tags. Since then, there has been a proliferation of RFID monitoring systems that measure individual animal feeding behavior, as well as individual DMI. Such systems (e.g., GrowSafe Systems, Airdrie, Alberta, Canada; Insentec—Roughage Intake Control [RIC], Hokofarm Group, Marknesse, Netherlands; Intergado Ltd., Contagem, Minas Gerais, Brazil) have facilitated collection of feeding behavior and DMI data on large groups of cattle with significantly less labor. Previous studies have used video monitoring to validate the accuracy of data collected using GrowSafe (Devries et al., 2003; Mendes et al. 2011), Insentec (Chapinal et al., 2007; Terman et al. 2021), and Intergado (Chizzotti et al., 2015; Olivera et al., 2018) monitoring systems. Despite their accuracy, the high capital and operating costs associated with such systems limit their use in commercial feedlot production.

Substantial research has focused on developing methodologies for predicting DMI. Previous research has used a pen-based approach to predict DMI. Pen-based approaches have used body weight (BW) and DMI for a given number of days on feed (DOF), resulting in a curvilinear relationship between DMI and DOF (Thornton et al., 1985; Hicks et al., 1990). Alternatively, overall BW and DMI feeding period averages have been used, resulting in a nearly linear relationship between DMI and DOF (McMeniman et al., 2010; Anele et al., 2014; NASEM, 2016). While such equations predict DMI reasonably well, a recent shift toward individual animal management (i.e., precision livestock production) necessitates DMI prediction on an individual animal basis.

Feeding behavior of cattle is highly repeatable from day-to-day (Hicks et al., 1987), and disruptions in DMI have been associated with erratic feeding behavior (Schwartzkopf-Genswein et al., 2003). Feeding behavior is intrinsically associated with DMI (Allen, 2014). Consequently, several individual animal DMI prediction models incorporate feeding behavior as a predictor (Davis et al., 2014; Halachimi et al., 2016; Davison et al., 2021). Numerous studies have investigated relationships between feeding behavior, DMI, and residual feed intake (RFI) in beef steers (Schwartzkopf-Genswein et al., 2002; Nkrumah et al., 2007; McGee et al., 2014; Kelly et al., 2020; Parsons et al., 2020). These studies evaluated feeding behavior using radio frequency identification (RFID) feed monitoring systems, where animals ate from individual feed bins, rather than a conventional linear bunk. Research investigating the effect of individual feed bins on feeding behavior in beef cattle is limited. Cruz et al. (2010) reported there were no differences in intake between individual and group feeding. But, in dairy cattle it has been shown that individual feeding stalls alter feeding behavior by decreasing feeding duration and the number of displacements at the bunk (DeVries and von Keyserlingk, 2006). As highlighted by Richeson et al. (2018) both the Insentec and GrowSafe systems utilize enclosed feeding areas, which may alter feeding behavior and typically requires substantial time for animals to acclimate.

Combining bunk cameras and sensors with machine learning algorithms in conventional feedlot production systems enables collection of high-resolution feeding behavior data on large groups of animals without disruption to natural feeding behavior (Tedeschi et al., 2021). Understanding differences in feeding behavior between conventional bunks and individual feeding bins is critical for developing DMI equations to accurately predict individual animal DMI under a variety of feeding systems. The objectives of the current study were to 1) compare feeding behavior measured using individual feed bins and from conventional bunks using cameras, and 2) evaluate relationships between feeding behavior, DMI, and animal performance.

MATERIALS AND METHODS

Animals and experimental design. All animals were managed in accordance with a University of California, Davis, Animal Care and Use Protocol (#22179). A single lot of Angus-cross steers (n = 132) estimated to be one year of age were purchased from an online video auction market. Steers were received at the University of California-Davis (UCD) feedyard on grass hay and allowed to rest 5 d before initial processing. At initial processing (d -1) steers were vaccinated with Inforce 3 (Zoetis Animal Health, Florham Park, NJ), Bovishield Gold One-Shot (Zoetis Animal Health, Florham Park, NJ), and Vision 8 + Somnus (Merck Animal Health, Rahway, NJ); given Dectomax Pour-on parasite treatment (Zoetis Animal Health, Florham Park, NJ); and implanted with Revalor-S (Merck Animal Health, Rahway, NJ). An initial body weight (BW), hip height (HH), and ultrasound measurements for back fat thickness (BF) and ribeye area

(REA) were taken on the left side at the interface of 12th to 13th rib with an Ibex Evo (E.I. Medical Imaging, Loveland, CO).

Cattle were stratified by BW and those weighing more than ±2 SD from the mean initial BW were excluded from the experiment. A total of 120 steers were used, with 24 steers assigned to feeding in an individual roughage intake control system (RIC, Insentec, Hokofarm Group B.V., Marknesse, the Netherlands) and 96 steers assigned to feeding in conventional bunks (CON). The RIC steers were randomly assigned to one of three pens (i.e., 8 steers/pen) with each steer was assigned its own unique feed bin to measure individual animal DMI. To select a unform set of steers for the RIC group, 48 steers surrounding the initial median BW (i.e., 24 steers above and 24 steers below) were used as an initial pool of candidates for the RIC group. The 48 steers were stratified by BW and randomly assigned to either RIC or CON group, for 24 steers in each group. The 24 steers assigned to the CON were recombined with the additional CON steers. This technique ensured similar initial mean shrunk body weight (SBW) for the 24 RIC steers and 96 CON steers (initial SBW = 346 and 345 kg, respectively).

The 96 CON steers were randomly assigned to one of eight pens with twelve steers in each pen. Half of the CON pens were equipped with Precision Livestock Technologies Inc. (Dallas, TX) camera modules. The solar-powered, WiFi-enabled camera modules were placed at bunk ends on poles at 4.6 m above the bunk. Two pens had a single camera module, and two pens had dual camera modules, one at each end of the bunk. Within pen, steers in the CON group were assigned uniquely colored ear tags and distinguishing back tag marking using colored adhesive estrus detection patches that were placed in varying location and color for identification using bunk cameras. The cameras captured bunk images at 1-min intervals from sun-up to sun-down. Data in the manuscript is only presented for the four pens that had bunk cameras (i.e., 48 steers).

All steers were placed in their respective pens on d 0, and RIC steers were given an Allflex (Irving, TX) RFID ear tag. Steers in the RIC system were gradually trained to use the gated feed bins over a 14-d period. Initially, the gates that allowed access to the feed bin were always open, so steers could access any feed bin. After gaining familiarity, steers were each assigned unique feed bins, and the gates were activated (i.e., closed), so feed access was only given if a specific RFID was scanned. For each individual steer feeding behavior and DMI were collected using RFID ear tag derived data, including access start and stop times, the length of the visit in seconds, and kilograms of feed consumed. These records were wirelessly transferred to a local computer where data files were available for download.

Ration composition is described in Table 3.1. Ration net energy for maintenance (NE_m) and gain (NE_g) were calculated using tabular values from NASEM (2016). For each new batch of total mixed ration a representative ration sample was collected and dried to calculate dry matter. Dry matter was calculated as the retained weight after drying in a forced air over for 36 h at 60°C. Steers were managed and transitioned following the same schedule: starting ration for 31 d, transitioning ration for 14 d, and finishing ration for a minimum of 84 d before harvest (Fig. 3.1). All cattle were fed twice daily (0630 and 1430), and RIC steers were fed at 10% greater than the previous days intake to ensure *ab libitum* feed access was provided. The CON steers were managed to a slick bunk (i.e., the amount of feed offered closely matches maximal feed intake of the cattle resulting in a 'slick' or empty feed bunk just before the next feeding time) to reflect management practices commonly used in commercial feedlot systems. Daily

DMI was recorded on an individual- and pen-basis for RIC and CON groups, respectively. Body weights, HH, and ultrasound measurements were taken every 28 d before morning feeding, and final measurements were taken the day before shipping for harvest.

Feeding behavior. Bunk visit (BV) frequency and duration were recorded by the RIC system and used to determine feeing behavior traits. Bunk visits were determined by the RIC system based on detection of RFID ear tags; the software recorded beginning and end time for each BV. The time between (i.e., interval) BV was defined as the non-feeding interval (NFI). When the NFI was less than 60 s, multiple BV were combined into a single BV event, and the end time was adjusted accordingly. This allowed comparison with the camera images that were taken at one-minute intervals. Maximal NFI was defined as the longest NFI within a day. After the BV data cleaning procedure, frequency of BV was defined as the total number of BV recorded in a 24-h period, regardless of whether feed was consumed or not. Mean BV duration was calculated. For the CON group, feeding behavior data was collected using camera images and reviewers for only the first 28 d on the finishing ration. Twelve reviewers were trained to evaluate bunk images frame-by-frame and record BV frequency and BV duration for each individual steer in a pen. Camera resolution and reviewer observations were validated as described by Harrison et al. (2022a).

Yeates et al. (2001) suggested grouping BV into meals using a meal criterion, where the meal criterion is defined by a between meal NFI that is greater than the within meal NFI. As proposed by Kelly et al. (2020), a two-pool bimodal probability density function was fit to $\log_{10}$-transformed NFI data using R statistical software (version 4.2.1). The meal criterion was defined as the intersection point between the two distributions. Meal criteria were calculated independently for the RIC and CON groups. After calculating the meal criteria, meal frequency and average meal duration were calculated.

Daily eating duration (ED) was defined as the sum of all BV in a day. Daily meal duration (MD) was defined as the sum of all meals in a day, and thus was always greater than ED. Since behavior measurements on the control cattle could not be collected overnight due to limited patch visibility, partial day (PD) feeding behavior traits were also calculated for RIC cattle. Behavior measurements on the CON group were conducted from sun-up (0600) to sun-down (2000), so PD eating behavior only included those fourteen hours, and data outside that time frame was excluded from PD feeding behavior trait calculations. A complete list of behavior traits is shown in Table 3.2.

Data management and statistical analysis All observed body weight measurements were reduced by 4% to estimate SBW. To reduce variation in weighing and measurement conditions, 28-d measurements for SBW, HH, BF, and REA were estimated for each day as the predicted value of the regression of each variable versus time for each animal. Estimates for empty body fat (EBF) were calculated using empty body weight (EBW) and regressed BF and REA values. Body composition and FS were calculated using equations listed in Table 3.3. Average daily gain (ADG) was calculated as the slope of the regression of SBW versus time. Residual feed intake (RFI) was defined as the residual of the regression of DMI on mid-test $SBW^{0.75}$ and ADG. Gain to feed ratio (G:F) was calculated individually for RIC steers and on a pen-basis for CON steers. To determine SBW and composition for the day cattle began the finishing ration, backward projections (d −12) were made using slope of the regression for each variable as the 28-d weight, HH, and ultrasound measures were made 12 days after transition to the finishing diet. Estimates for maintenance energy (i.e., alpha where NE_m is defined as alpha × $EBW^{.75}$) were obtained from Harrison et al. (2022b).

Data analysis and graphic visualization were performed in R (version 4.2.1). Day-to-day variation in feeding behavior traits and DMI was computed using individual animal linear regressions to regress each feeding behavior trait on day of trial. As proposed by Putz et al. (2019), daily variation was defined as the root mean squared error (RMSE) of the residuals from the regression using a *for loop* in the base R package. To evaluate the effect of feeding system on performance, feed efficiency, and body composition, a *t*-test was used to compare RIC and CON group means. For comparison of feeding behavior between groups, individual animal feeding behavior traits for PD-RIC and CON groups were averaged across animal by day, for a total of twenty-six daily observations in each group. Two days from the twenty-eight days of data were omitted due to camera malfunction. A *t*-test was used to evaluate the effect of feeding system (i.e., individual or conventional feed bunks) on feeding behavior traits shown in Table 3.2. Data from only the RIC steers for the entire 84 d feeding period was used to calculate Pearson correlation coefficients for performance, feed efficiency, feeding behavior, and daily variation in feeding behavior were generated in the multivariate platform of JMP (SAS Inst. Inc., Cary, NC). Significance was declared at $P < 0.05$.

RESULTS AND DISCUSSION

Performance. Estimated means and SD for performance, feed efficiency, and body composition for RIC and CON steers are shown in Table 3.4. By design, the variation in initial mean SBW was numerically lower for the RIC cattle as compared to the CON cattle (SD = 12 and 31 kg, respectively), as the RIC cattle were specifically selected to be a uniform subset but, means did not significantly differ for initial or final SBW (P = 0.50 and P = 0.40, respectively). Mean HH was greater (P = 0.02) for CON cattle. Overall mean and SD for ADG was 1.87 ± 0.29, with no difference detected between groups (P = 0.20). These results are consistent with Cruz et al. (2010) that reported no difference in ADG between animals fed individually and in group pens. In the current study, variation in metabolic BW and ADG explained 66% of variation in DMI, which was consistent with values reported in recent studies (Hafla et al., 2013; Dykier, 2017; Herd et al., 2019).

When DMI was compared over the initial 28-d period and the entire feeding period, DMI was significantly lower for the CON steers compared to the RIC cattle (P = 0.002 and P = 0.036, respectively; Table 3.4). Differences in DMI could be due to differences in bunk management, as it has been well documented in the literature that limit feeding, which has evolved into slick bunk management, improves feed efficiency in comparison to *ad libitum* feeding (Galyean et al., 1999; Schwartzkopf-Genswein et al., 2011; Owens and Hicks, 2019). However, the altered feeding environment and limited social hierarchy effects (i.e., no competition for bunk space) may also have also contributed to increased intake for RIC steers but confounding of management and feed bunk type make it impossible to discern. In a comparison of steers fed individually and using a feeding trough, Gonyou and Stricklin (1981) reported no differences in DMI. In this study, individually fed steers all had to compete for feed from a single trough, which may have impacted results. Such results were reaffirmed by Cruz et al. (2010) that reported no differences in DMI between individual and group feeding.

Daily variation in DMI was significantly lower (P < 0.001) in the CON group as compared to the RIC steers (Table 3.4). These results were expected since CON dry matter intake reflects daily intake at the pen level, which is highly repeatable (Hicks et al., 1987; Periera et al., 2021). In a study using 238 pens of bulls, daily intake fluctuations ranged from 2.1 to 14.8%, with a mean of 5.7% (Periera et al., 2021). For animals fed individually in a RIC system, Lahart et al. (2020) reported daily DMI fluctuated by 16.2%. In the current study, mean intake fluctuations were 13.3 and 9.0% for the RIC and CON groups, respectively. It is important to note that with pen-feeding although DMI fluctuations are reduced, at the individual animal level DMI fluctuations are still present, but these individual animal changes are masked by the pen feed call.

There was no difference (P = 0.75) in G:F between groups. Maintenance requirements for the RIC were 10% greater than the CON cattle, though the increase was not significant (P = 0.20). Residual feed intake mean and SD were 0.0 and 0.52 kg for the RIC cattle, which is consistent with previously reported RFI for cattle of similar age and breeds (McGee et al., 2014; Kelly et al., 2020). Initial BF (P = 0.05) and initial EBF percent (P < 0.001) were both lower in the CON as compared to the RIC group. At the end of the feeding period, there was a tendency for lower final BF (P = 0.09) and EBF percent (P = 0.07), and final REA was greater (P < 0.001) in CON as compared to RIC steers. Despite a tendency for a lower final BF and EBF percent in CON as compared to RIC steers, there was no difference in marbling score between groups (P = 0.61). These results are consistent with Brethour (2004) who reported no relationship between BF and marbling score. Although BF is correlated with EBF percent, marbling is largely independent of BF, predominantly dictated by genetics and prenatal adipocyte formation (Nguyen et al., 2021).

Feeding behavior between groups. Descriptive statistics for feeding behavior traits are presented in Table 3.5. Mean daily eating duration (ED) ranged from 73 to 140 min/d. This is consistent with the range previously reported in the literature (Schwartzkopf-Genswein et al., 2002; Kelly et al., 2020; Parsons et al., 2020). For direct comparison between RIC and CON groups, PD-RIC feeding behavior traits were calculated (Table 3.5). Among RIC steers, 85% of daily ED occurred during daylight hours (i.e., 6000 to 2000). Meal criteria were determined to be 6.6, 5.3, and 9.4 min for 24-h RIC, PD-RIC, and CON groups, respectively. Current results suggest 42% increase in meal criterion for CON steers compared to 24-h RIC observations, and an even greater increase when compared to PD-RIC observations. Meal criteria in the current study was less than the range of 11.9 to 23.9 min previously reported for similar methods (Kelly et al., 2020; Parsons et al., 2020). However, in both of those previous studies, not all animals within a pen could not simultaneously access feed; stocking density ranged from 2 to 9 animals per feed bin. In the current study all RIC steers had access to their own feed bin, which eliminated competition at the feed bin, facilitating a more casual eating pattern, marked by a greater frequency of smaller visits to the feed bin. To eliminate such differences, Schwartzkopf-Genswein et al. (2002) recommended a standard meal criterion of 5 minutes, but this may not accurately reflect feeding behavior patterns.

A comparison between PD-RIC and CON eating behavior traits is shown in Table 3.6. Compared to the RIC group, CON steers had greater ($P < 0.001$) partial daily ED, BV length, and mean meal duration. Similar to the current study, Gonyou and Stricklin (1981) reported cattle fed individually had decreased daily ED. For CON steers, the greater BV duration was accompanied by a lesser BV frequency ($P < 0.001$), but there was no difference ($P = 0.22$) in meal frequency between PD-RIC and CON groups. In other words, cattle that ate less frequently, spent longer eating each visit to the bunk. This phenomenon was described by Schwartzkopf-Genswein et al. (2003), where limiting feed access caused cattle to shift feeding patterns and consume feed in a fewer number of longer feeding bouts. When feed access is limited increases in eating rate (ER) and decreases in meal frequency have commonly been reported (Gibb et al., 1998; Fanning et al., 1999; Schwartzkopf-Genswein et al., 2002). Due to greater competition with feed restriction, cattle consumed feed faster in larger meals to ensure they get their fill. Carvalho and Felix (2021) reported an ER of 136 g/min for Holstein steers fed individually fed using slick bunk management. Eating rate could not be calculated for the CON steers since individual DMI was unknown. For the RIC steers, mean (± SD) ER was 115 ± 21 g/min. In the RIC cattle there was no feeding competition, and cattle ate short, slow, frequent meals. Parsons et al. (2020) reported a range in ER of 159 to 170 g/min in steers individually fed *ad libitum,* but steers had a high stocking density at 8.5 steers per feed bin. When comparing cattle fed *ad libitum* in individually and in group pens, Gonyou and Stricklin (1981) reported cattle fed individually had increased ER. Such results suggest bunk management and stocking density have an impact on eating rate and eating patterns.

Relationships between feeding behavior and intake. Correlations between daily DMI, feeding behavior, and body composition using daily data from the RIC cattle for the entire 84-d feeding period are summarized in Table 3.7. The relationships between DMI and ED (r = 0.37) and ER (r = 0.32) were both nonsignificant. Daily ED only explained 14% of the variation in DMI. These results are similar to previous studies that reported poor relationships between ED and DMI (Gibb et al., 1988; Schwartzkopf-Genswein et al., 2002). By itself, daily ED is a poor indicator of feed intake. Daily ED was strongly correlated with ER (*r* = −0.73), suggesting steers that eat faster, spend less total time a day eating. The same relationship was observed by Schwartzkopf-Genswein et al., (2002) and Kelly et al., (2020). However, from a practical standpoint this adds little value for DMI prediction, as eating rate cannot be calculated without the amount of feed consumed known.

When daily DMI was correlated with daily body composition as determined using the DGM, there was no relationship (*r* = 0.01) between DMI and EBF percent (Table 3.7). This is contrary to feed intake curves reported by Hicks et al. (1990), where DMI deceased with increased percent EBF over the feeding period. A similar relationship was reported by Owen et al. (1995), suggesting growth and intake plateaus at a given level of body fatness. However, the cattle in the current study had slightly greater initial BW and significantly greater final BW than those reported by Hicks et al. (1990). In the current study there was also no relationship between DMI and EBW (*r* = −0.06), which is consistent with previous studies that have shown EBW is a marginal predictor of DMI (Anele et al., 2014; Davis et al., 2019). Correlations between BV frequency and mean BV duration (*r* = −0.78) and meal frequency and mean meal duration (*r* = −0.68) were strongly negative. As previously described, feeding bout (i.e., BV or meal) frequency and duration were inversely associated, so animals that ate more frequently ate less time each visit. This relationship was true for both RIC and CON steers (Table 3.5), indicating such eating patterns exist regardless of type of bunk management.

Correlation coefficients for feeding behavior, performance, and daily variation in feeding behavior traits over the entire feeding period are shown in Table 3.8. While unimportant at the daily level, correlations based on feeding period averages were significant for DMI (*P* = 0.003) and ER (r = 0.58). Eating rate was also moderately correlated (r = 0.46; P = 0.02) with ADG. Previous studies also reported increased ER rates for high ADG steers (Schwartzkopf-Genswein et al., 2002; Hickman, 2003). Conversely, Kelly et al. (2020) reported little relationship between ER and ADG. Data from the current study also suggested a trend (P = 0.06) in slower ER in low RFI steers. Kelly et al. (2020) reported a positive correlation coefficient for ER and RFI, similar to the value in the current study. Conversely, a negative relationship between ER and RFI was reported by Parsons et al. (2020). In the current study, cattle with low RFI were also characterized by a trend toward greater (P = 0.08) BV frequency and lesser (P = 0.02) mean BV duration. This pattern (i.e., a larger number of smaller meals) has been consistently associated with improved efficiency and RFI (McGee et al., 2014; Kelly et al., 2020). In general, both heavier cattle and faster-growing cattle consumed more feed per meal, but specific eating patterns seemed to be dictated by efficient and inefficient animals. Such research suggests feeding behavior may be a suitable for proxy for RFI in conventionally fed cattle when measuring DMI is not possible.

Between-animal variation in maintenance requirements have been thoroughly documented in the literature (Jenkins and Ferrel, 1985; Guinguina et al., 2020; Cabezas-Garcia et al., 2021). However, the effects of individual animal feeding behavior on maintenance requirements have not been well investigated. Correlation coefficients for maintenance energy requirements (i.e., alpha) and feeding behavior traits are shown in Table 3.8. Daily ED (r = −0.12) and ER (r = −0.02) had a weak, negative correlation with alpha. With respect to BV traits, daily BV frequency was positively correlated (r = 0.23), but mean BV duration was negatively correlated (r = −0.29) with alpha. There was a tendency (P = 0.07) for steers with decreased alpha to consume less feed per BV, although the relationship between ER and alpha was not significant. Although, previous studies have not considered the relationship between maintenance requirements and feeding behavior, McGee et al. (2014) used progeny from bulls selected for low and high NE_m. Contrary to the current study, it was reported that progeny from high NE_m bulls had longer BV with a tendency to consume more feed per visit. In comparison to the current study, bulls used by McGee et al. (2014) had greater competition for bunk space, which likely contributed to divergent results. Further, since maintenance requirements were not estimated for individual steers, individual steer maintenance energy requirements and RFI could not be compared. Further research is needed to determine the relationship between feeding behavior and maintenance energy requirements.

Correlations for day-to-day variation (measured as RMSE) in eating behavior and performance are shown in Table 3.8. Steers with lower DMI had greater ($P = 0.05$) day-to-day variation in total meal duration ($r = -0.40$), and a tendency ($P < 0.10$) for greater total daily ED ($r = -0.35$) and mean meal duration ($r = -0.36$). Decreased DMI might be a result of variability in the ruminal environment that was caused by the erratic feeding patterns (Schwartzkopf-Genswein et al., 2003). Conversely, Parsons et al. (2020) reported positive correlations between DMI and daily variation in BV frequency, BV duration, meal frequency, and meal duration, albeit the correlation values were low. However, as previously described, feeding patterns differed in that study, and ER was not associated with ADG or RFI. In the present study, less day-to-day variation in BV frequency tended ($P = 0.06$) to be associated with improved G:F and RFI. Similarly, high RFI steers tended to have increased daily variation in BV ($P < 0.10$). These results are consistent with previously described frequency and duration trends among BV and meal events. Consistent intake patterns likely contributed to reduced volatility in the ruminal environment, which resulted in improved efficiency.

Most commercial feedlots use slick bunk management, which essentially requires a slight feed restriction, and with that feed intake of animals at the low end of the hierarchy may be more affected than dominant animals, especially when competing in a feed intake monitoring system when all animals can't simultaneously access feed. Many bulls are genetically tested for RFI using automated feed intake monitoring systems, so it is important to ensure the relative efficiency ranks between animals do not change when animals are fed in groups. Further, bull tests are conducted using a variety of ration types, and ration type has been shown to affect feeding behavior in beef cattle (Goulart et al., 2020). Thus, it is critical to ensure the results and rankings from bull testing is not affected by conditions of the bull test (i.e., feeding system and ration type). The accuracy of measuring feeding behavior and efficiency in bulls has important implications for seedstock operators and feedlot producers.

CONCLUSIONS AND IMPLICATIONS

Results from this study indicate distinct differences between feeding behavior patterns in steers fed using the RIC system and conventional bunks. Conventional cattle had a smaller number of longer feeding bouts, but total daily eating duration was greater and DMI was decreased compared to the RIC steers. Cattle with low RFI tended to have greater BV frequency and lesser mean BV duration. Current results suggest a substantial amount of phenotypic variation in feeding behavior, both between and within animals. With emerging technologies that monitor individual animal feeding behavior using RFID tags in conventional bunks, knowledge of phenotypic and genetic correlations between feeding behavior and DMI are critical. Future research should investigate differences in individual feeding under a variety of stocking densities and feeding regimes, as well as a greater understanding of causes and effects associated with different feeding mechanisms.

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FIGURES

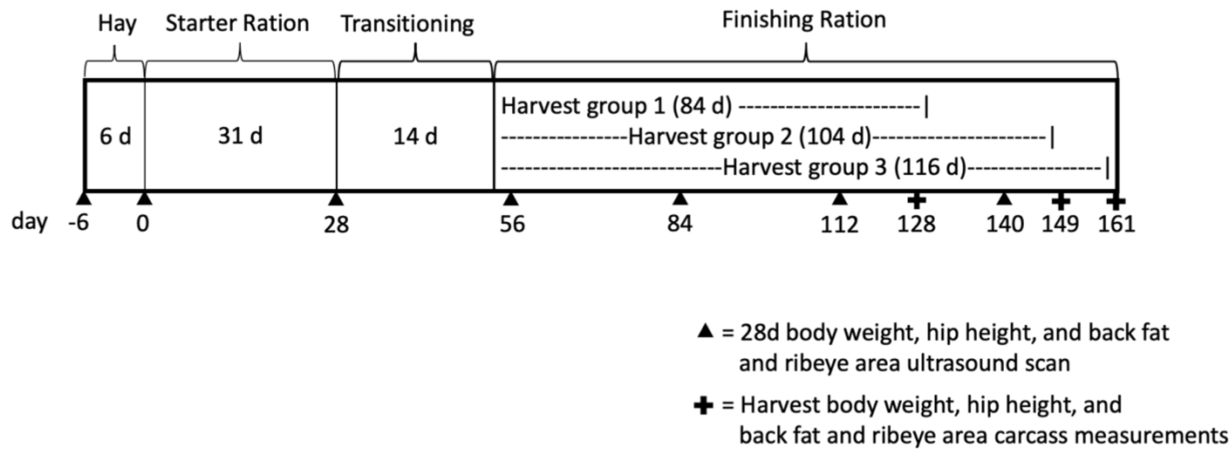

Figure 3.1. Project timeline

Table 3.1. Ration composition on a percent *dry matter basis*

Parameter	Starter	Transitioning	Finisher
Rolled Corn, %	41.99	51.12	72.00
Dried distillers grains, %	20.00	20.00	6.00
Wheat hay, %	15.00	8.00	6.00
Alfalfa hay, %	12.00	10.00	5.00
Yellow grease, %	1.50	2.00	3.00
Molasses, %	8.00	7.00	3.00
Urea, %	0.35	0.40	1.80
Beef trace salt, %	0.32	0.32	1.00
Rumensin, %	0.02	0.02	0.02
Calcium carbonate, %	0.82	1.15	1.80
Magnesium oxide, %	0.32	0.00	0.02
Potassium chloride, %	0.00	0.00	0.50
Ration energy, Mcal/ kg DM			
Maintenance net energy	1.88	1.98	2.02
Gain net energy	1.24	1.33	1.38

Table 3.2. Definitions of feeding behavior traits evaluated in the study

Type	Trait	Definition
Daily traits	Eating duration (ED), min/d	Sum of the durations of BV events recorded each 24 h period
	Max non-feeding interval (NFI)	Maximum non-feeding interval each 24 h period
Bunk visit traits	BV frequency, events/d	Number of BV events recorded each day
	Mean BV duration, min/event	Average length of BV events
Meal traits	Meal frequency, events/d	Number of meal events recorded each day
	Meal duration, min/d	Sum of the duration of meal events recorded each day
	Mean meal duration, min/meal	Average length of meal event
Partial-day[1]	Eating duration, min/partial d	Sum of the durations of BV events recorded each daylight (14 h) period
	BV frequency, events/partial d	Number of BV events recorded each daylight (14 h) period
	Meal frequency, events/partial d	Number of meal events recorded each daylight (14 h) period
	Meal duration, min/partial d	Sum of the duration of meal events recorded each daylight (14 h) period

[1]Partial day are based on daylight hours (i.e., 0600 to 2000) for comparison between roughage intake control (RIC) and conventional (CON) pens

Table 3.3. Equations used to estimate body composition and energy use

Term	Equation	Literature Cited
Metabolic body weight, kg	$MBW = SBW^{0.75}$	Kleiber (1947)
Empty body weight, kg	$EBW = 0.917 * SBW - 11.39$	Owens et al. (1995)
Frame Size	$FS = -11.548 + (0.4878 * HH/2.54) - (0.0289 * AGE) + (0.00001947 * AGE^2) + 0.0000334 * HH * AGE$	Cundiff et al. (2010)
Empty body fat, kg	$EBF = (0.351 * EBW) + (21.6 * YG) - 80.8$	Perry and Fox (1997)

Table 3.4. Effect of feeding in a roughage intake control system (RIC) and conventional feed bunks (CON) on performance, feed efficiency, and maintenance energy in steers fed a high-concentrate diet

Traits	RIC	CON	SE	*P*-value
N=	24	48	-	-
Performance traits				
Initial shrunk body weight, kg	438	435	6.6	0.496
Final shrunk body weight, kg	598	605	9.6	0.402
Mean hip height, cm	131.3	133.1	0.75	0.020
Average daily gain, kg/d	1.92	1.84	0.07	0.199
Dry matter intake (DMI) and efficiency				
28-d DMI, kg/d	11.92	11.45	0.103	0.002
Feed period DMI, kg/d	11.57	10.81	0.302	0.036
DMI root mean square error, kg/d	1.37	0.53	0.101	<0.001
Maintenance net energy, Mcal/kg$^{0.75}$	0.0962	0.0875	0.015	0.198
Gain:Feed	0.166	0.167	0.004	0.750
Composition traits				
Initial back fat thickness, cm	0.80	0.74	0.029	0.045
Final back fat thickness, cm	1.71	1.58	0.075	0.086
Initial empty body fat, %	25.13	22.16	0.743	<0.001
Final empty body fat, %	32.16	31.09	0.624	0.073
Initial ribeye area, cm^2	64.24	63.93	1.444	0.832
Final ribeye area, cm^2	87.95	91.92	1.650	0.015

Table 3.5. Means and SD and calculated meal criterion for feeding behavior traits for steers fed a high-concentrate diet individually in a roughage intake control system (RIC) and conventional feed bunks (CON)

Traits	24 h RIC[1]	Patrial day RIC[2]	CON[2]
Eating duration, min/d	110 ± 6.6	94 ± 6.6	110 ± 14.2
Bunk visit frequency, events/d	14.8 ± 1.1	12.1 ±1.3	10.5 ± 1.2
Mean bunk visit duration, min/event	8.3 ± 0.5	8.9 ± 0.82	11.0 ± 1.1
Meal criterion, min	6.6	5.3	9.4
Meal frequency events/d	9.5 ± 5.5	7.7 ± 0.61	7.9 ± 0.48
Mean meal duration, min/meal	13.2 ± 0.72	12.9 ± 0.82	14.5 ± 1.6

[1]Observations over a 24 h-period

[2]Observations over a 14-h hour daylight period, 0600 to 2000

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Table 3.6. Effect of feeding in a roughage intake control system (RIC) and conventional feed bunks (CON) on feeding behavior traits pooled by day in steers fed a high-concentrate diet

Traits	PD-RIC[1]	CON	SE	*P*-value
Eating duration, min/d	94.3	110.2	3.333	<0.001
Bunk visit frequency, events/d	12.1	10.5	0.363	<0.001
Mean bunk visit duration, min/event	8.9	11.0	0.292	<0.001
Meal frequency, events/d	7.6	7.9	0.165	0.222
Mean meal duration, min/meal	12.9	14.5	0.390	<0.001

[1] Partial day RIC traits were calculated from 0600 to 2000 to match the CON observations

Table 3.7. Pearson correlation coefficients for *daily* feeding behavior traits and *daily* body composition for steers fed a high concentrate diet

	EBW[1]	EBF%[2]	ED[3]	DMI[4]	ER[5]	Max NFI[6]	BV FREQ[7]	Mean BV DUR[8]	Meal FREQ[9]	Mean Meal DUR[10]	MD[11]
Eating duration	−0.30*	−0.29*	1.00								
Dry matter intake	−0.06*	0.01	0.37*	1.00							
Eating rate	0.27*	0.30*	−0.73*	0.32*	1.00						
Max NFI	0.29*	0.15*	−0.18*	−0.15*	0.06	1.00					
BV frequency	−0.23*	−0.23	−0.04	0.18*	0.18*	−0.19*	1.00				
Mean BV duration	0.04	0.04	0.50*	0.00	−0.51*	0.13*	−0.78*	1.00			
Meal frequency	−0.45*	−0.32*	0.33*	0.25*	−0.15*	−0.37*	0.56*	−0.33*	1.00		
Mean meal duration	0.20*	0.06	0.36*	0.02	−0.35*	0.25*	−0.34*	0.53*	−0.68*	1.00	
Meal duration	−0.34*	−0.35*	0.93*	0.38*	−0.65*	−0.19*	0.27*	0.24*	0.40*	0.35*	1.00

[1] Empty body weight
[2] Empty body fat percent
[3] Eating duration
[4] Dry matter intake
[5] Eating rate
[6] Maximum non-feeding interval
[7] Bunk visit frequency
[8] Mean bunk visit frequency
[9] Meal frequency
[10] Mean meal duration
[11] Meal duration
*Correlations are different from zero at $P < 0.05$.

Table 3.8. Pearson correlation coefficients for feeding behavior, production, and daily variation in feeding behavior traits for steers fed a high concentrate diet

Parameter	Dry matter intake	Alpha	Average daily gain	Gain:Feed	Residual feed intake
Dry matter intake	1.00	−0.19	0.78*	0.24	0.58*
Empty body weight	0.61*	−0.37	0.62*	0.37	−0.05
Empty body fat, %	0.45*	−0.28	0.46*	0.28	0.04
Eating duration	−0.17	−0.12	−0.13	−0.04	0.20
Eating rate	0.58*	−0.02	0.47*	0.16	0.40
Max non-feeding interval	−0.22	0.09	−0.10	0.04	−0.28
Bunk visit frequency	0.03	0.24	−0.12	−0.22	0.36
Mean bunk visit duration	−0.19	−0.28	0.00	0.19	−0.46*
Meal frequency	0.24	−0.12	0.18	0.06	0.27
Mean meal duration	−0.39	0.07	−0.34	−0.17	−0.30
Meal duration	−0.24	0.00	−0.26	0.36	−0.11
Day-to-day variation (RMSE[1])					
Eating duration RMSE	−0.35	−0.10	−0.27	−0.09	−0.31
Bunk visit frequency RMSE	−0.09	0.40	−0.29	−0.38	0.38
Mean bunk visit duration RMSE	−0.22	−0.15	−0.07	0.07	−0.38
Meal frequency RMSE	0.09	0.06	0.09	0.03	0.11
Mean meal duration RMSE	−0.36	−0.03	−0.19	0.02	0.01
Meal duration RMSE	−0.40	0.00	−0.38	−0.20	−0.24

*Correlations are different from zero at $P < 0.05$.

[1] RMSE = root mean square error

CHAPTER IV: INFLUENCE OF GROWTH PATTERNS ON MARKETING AND PROFITABILITY

INTRODUCTION

Determination of the optimal marketing for feedlot cattle is a complex decision process dependent on cattle growth and development, production factors, and dynamic pricing structures. Live body weight (BW), body fatness, and marbling score have been shown to increase with longer feeding periods (Van Koevering et al., 1995; Owen and Gardner, 2000; Tatum et al., 2012). However, increased days on feed (DOF) is also associated with a greater number of overweight and USDA Yield Grade (YG) 4 carcasses (Hicks et al., 1987), which has a negative effect on profitability. To improve carcass quality and uniformity, many feedlot producers sell cattle using a value-based grid that awards premiums and discounts based on USDA Quality Grade (QG) and YG (Tatum et al., 2006). In many grids carcasses are discounted for inadequate marbling, excessive fat, and failure to meet carcass weight specifications. Suboptimal marketing can significantly impact expected profits from cattle genetics, production practices, and management decisions.

Feedlot cattle in the United States are typically fed between 90 and 300 DOF (USDA, 2018). Marketing decisions are made based on observed BW, visual appraisal of body fatness, and modeling techniques. With longer feeding periods and increased body fatness, cattle average daily gain (ADG) declines and efficiency decreases (Van Koevering et al., 1995; Pyatt et al., 2005). Visual appraisal of 0.40 to 0.50-inch (i.e., 0.9 to 1.1 cm) back fat thickness (BF) has been used as rule of thumb to determine harvest readiness (Maples et al., 2015; Wilken et al., 2015; Bondurant et al., 2016). Similarly, 28.6% empty body fat (EBF) is commonly used as a target EBF percent for harvest, as it has been established to be sufficient to achieve a USDA QG of low choice (Perry and Fox, 1997; Guiroy et al., 2001). However, these rule of thumb marketing strategies attempt to maximize profits by reducing the risk over-finished carcasses rather than pinpointing optimal marketing time.

A substantial amount of literature has focused on developing modeling methods to predict the optimal timing of harvest (Sainz and Oltjen, 1994; Tedeschi et al., 2004; Garcia et al., 2005; Maples et al., 2015; Poss et al., 2022). Previous techniques have primarily based marketing decisions on average performance at a pen-level basis. But with emerging precision livestock technologies, individual animal BW, body composition, and dry matter intake (DMI) data can be collected in real-time, and optimal marketing time can be predicted on an individual animal basis (Sainz, 2019). Optimal marketing time can be defined as the date at which the cost of gain is equal to the price received for additional gain (Wilken et al., 2015), which will vary for each individual animal depending on DMI, growth, and body composition.

The objective of this paper was to describe the development and evaluation of dynamic mechanistic growth curves to predict daily growth, body composition, and DMI for use in evaluation of marketing decisions and profitability. Specific objectives were to 1) develop growth and cost curves, 2) evaluate the effect of optimal harvest timing at a pen and individual level, and 3) compare the effects of sorting by BW and DOF on performance and profitability.

MATERIALS AND METHODS

Animals and experimental design. All animals were managed in accordance with a University of California, Davis, Animal Care and Use Protocol (#22179). A single lot of Angus-cross steers (n = 132) estimated to be one year of age were purchased from an online video auction market. Steers were received at the University of California-Davis (UCD) feedyard on grass hay and allowed to rest 5 d before initial processing. At initial processing (d −1) steers were vaccinated with Inforce 3 (Zoetis Animal Health, Florham Park, NJ), Bovishield Gold One-Shot (Zoetis Animal Health, Florham Park, NJ), and Vision 8 + Somnus (Merck Animal Health, Rahway, NJ); given Dectomax Pour-on parasite treatment (Zoetis Animal Health, Florham Park, NJ); and implanted with Revalor-S (Merck Animal Health, Rahway, NJ). An initial body weight (BW), hip height (HH), and ultrasound measurement for BF and ribeye area (REA) were taken. Ultrasound measurements were taken on the left side at the interface of 12^{th} to 13^{th} rib with an Ibex Evo (E.I. Medical Imaging, Loveland, CO).

Cattle were stratified by BW and those weighing ±2 SD from the mean initial BW were excluded from the experiment. A total of 120 steers were used, with 24 steers assigned to feeding in a roughage intake control system ([RIC], Insentec, Hokofarm Group B. V., Marknesse, the Netherlands) and 96 steers assigned to feeding in conventional bunks (CON). Steers in the RIC group were randomly assigned to one of three pens (i.e., 8 steers/pen), and each steer was given a radio frequency identification (RFID) ear tag for access to a unique, individual feed bin. To select a unform set of steers for the RIC group, 48 steers surrounding the initial median BW (i.e., 24 steers above and 24 steers below) were used as an initial pool of candidates for the RIC group. The 48 steers were stratified by BW and randomly assigned to either RIC or CON group, for 24 steers in each group. The 24 steers assigned to the CON were recombined with the additional CON steers. This technique ensured similar initial mean shrunk body weight (SBW) for the 24 RIC steers and 96 CON steers (initial SBW = 346 and 345 kg, respectively).

The 96 CON steers were randomly assigned to sorting by BW or expected days on feed (DOF). Steers within BW and DOF sort groups were randomly assigned to one of two replicates.

Within replicate, BW groups were divided into light (initial SBW = 323 kg) and heavy (initial SBW = 366 kg) pens, and DOF groups were divided into short and long pens, for a total of 8 pens with 12 steers in each pen (Fig. 4.1). Expected DOF was determined by use of the Davis Growth Model (Oltjen et al., 1986) using initial body measurements for BW, HH, BF, and REA. Predicted DOF were 119 and 160 d for and long and short groups, respectively. All animal allocation and sorting were done based on BW and measurements take on d −1, and all steers were placed in their respective pens on d 0.

Ration composition is described in Table 4.1. Ration net energy for maintenance and gain were calculated using tabular values from NASEM (2016). Steers were managed and transitioned following the same schedule: starting ration for 31 d, transitioning ration for 14 d, and finishing ration for a minimum of 84 d before harvest (Fig. 4.2). All cattle were fed twice daily (0630 and 1430), and RIC steers were fed at 10% greater than the previous days intake to ensure *ab libitum* feed access was provided. The CON steers were managed to a slick bunk (i.e., the amount of feed offered closely matches maximal feed intake of the cattle resulting in a 'slick' or empty feed bunk just before the next feeding time) to reflect management practices commonly used in commercial feedlot systems. Daily DMI was recorded on an individual- and pen-basis for RIC and CON groups, respectively. Body weights, HH, and ultrasound measurements were taken every 28 d before morning feeding, and final measurements were taken the day before shipping for harvest.

Cattle were marketed in three groups when they were deemed market ready by means of visual appraisal with consideration of pen mean BW and BF (Fig. 4.2). Based on industry averages for similar frame-sized cattle, a mean pen BW of 634 kg was targeted for heavy body weight pens and 612 kg was targeted for all other pens. Back fat thickness target was 1.1 cm for all groups. Cattle were harvested at a commercial abattoir (Cargill Meat Solutions, Fresno, CA). At harvest, hot carcass weight (HCW) and USDA QG were recorded. Marbling score (MA) was measured by a trained evaluator following USDA (2019) guidelines. Back fat thickness and REA were measured. All carcass measurements and evaluation were performed on the left carcass side.

Model building and assumptions. Observed BW measurements were reduced by 4% to determine SBW. Empty body weight (EBW) was calculated using an equation from Owens et al. (1995):

$$EBW = 0.917 * SBW - 11.39 \qquad \text{[Eq. 1]}$$

After calculating EBW, empty body fat in kilograms was calculated using the equation:

$$EBF_i = (0.00128 * EBW_i^{1.88237}) + (21.26 * (BF_i - (-2.00155 + (0.007153 * EBW_i)))) + (-1.0714 * (REA_i - (6.79886 + 0.15009 * EBW_i))) \qquad \text{[Eq. 2]}$$

Empty body fat percent was estimated using calculated EBF in kilograms and EBW. Growth curves for SBW, BF, REA, and EBF percent were individually estimated for each steer and pen using repeated measure data from the finishing ration. To evaluate the optimal marketing time, which was defined as the day of maximum profit, growth prediction curves were used to simulate a feeding period of 200 d. Growth curves were fit in R (version 4.2.1) using a *for loop* function in the base package. Dry matter intake curves were computed on an individual and pen-basis for RIC and CON groups, respectively. For the CON pens when individual DMI was unavailable, an adapted DMI equation was used from Hicks et al. (1990):

$$DMI = 0.011 * (\text{Initial SBW} - 318) + 8.7965 + 0.016605 * DAY - 0.000094225*DAY^2 + 0.0000001375*DAY^3 \quad \text{[Eq. 3]}$$

Equation 3 was also used to predict DMI for the RIC steers beyond the point of harvest to develop cost curves. Average daily gain was estimated daily using the Davis Growth Model (Oltjen et al., 1986) and individual steer parameter estimates for net energy for maintenance (alpha) and protein synthesis (K2) were obtained from Harrison and Oltjen (2022).

Yield grade and QG were estimated for each day of the feeding period. Yield grade was calculated using an EBF percent-based equation that was adapted from Fox and Black (1984):

$$YG = -1.6 + 0.162(EBF_{percent}) \quad \text{[Eq. 4]}$$

This equation was chosen over the standard USDA Yield Grade equation that uses hot carcass weight (HCW); BF; REA; and percent kidney, pelvic, and heart fat (KPH), since KPH could not be measured on growing steers. Quality grade was estimated using EBF percent and a modified version of an equation from Fox and Black (1984):

$$QG = -4.415 + 0.25(EBF_{percent}) \quad \text{[Eq. 5]}$$

Based on the above equation, QG were as follows: Standard: < 9.5, Select: 9.5 to 10.5, Low Choice 10.5 to 11.5, Mid Choice: 11.5 to 12.5, High Choice: 12.5 to 13.5 and ≥ 13.5 Prime. Hot carcass weight was calculated using predicted SBW and a dressing percent of 62%, which was the observed mean dressing percent in the current study.

Economic and statistical analysis. Profit was calculated as carcass value minus costs, but maximum profit or minimum loss was determined to be the day that the daily change in carcass value became equal or less than the additional daily costs of feeding, or when marginal costs exceed marginal revenue. Prices used in the carcass valuation are shown in Table 4.2. Base price assumed a YG 3 and QG of Choice. Carcass weights greater than 413 kg were discounted, and carcass weights greater than 433 kg were discounted more severely. Base price, premiums, and discounts were 5-year averages obtained from USDA (2020). Marginal costs included the steer purchase price and feed costs. Steers were purchased at $150/45.4 kg, and the pay weight was 352 kg. Feed costs (including yardage) were assumed to be $0.18/kg (Lardy, 2018), which was consistent with feed prices paid in the current study.

All statistical analysis and graphic visualization were done in R version (4.2.1). Graphs were generated using the ggplot2 package. For comparison of the BW and DOF sorting treatments, means and SD were calculated by pen and sort treatment means were compared using a *t*-test with pen as the experimental unit. Sort treatment variance was compared using an *F*-test with pen as the experimental unit. The criteria R^2 and root mean square error (RMSE) were used to assess growth models. Significance was declared at $P < 0.05$.

RESULTS AND DISCUSSION

Performance. The RIC steers were harvested after 84 d on the finishing ration. Conventional steers were harvested in three different groups. In group one, both heavy-BW sort pens and both short-DOF sort pens were harvested after 84 d on the finishing ration. In group two, both long-DOF sort pens and one light-BW sort pen was harvested after 104 d on the finishing ration, and in group 3, the final light-BW sort pen was harvested after 116 d on the finishing ration. Performance data summarized by DOF is shown in Table 4.3. Initial SBW was numerically differed by sort group, with an inverse relationship between DOF and initial SBW. Since pens were harvested at a target BW, lighter pens took longer to reach the target BW.

Combining all groups, mean and SD final BW was 603 and 37 kg, respectively. Dry matter intake for steers harvested at 84 d was 13% greater, compared to steers harvested at 102 and 116 d. Similarly, ADG for RIC and CON groups harvested at 84 d (ADG = 1.92 and 1.91, respectively) was greater than groups harvested at 102 and 116 d (ADG = 1.71 and 1.64, respectively). Inverse relationships between DMI and DOF and ADG and DOF have also been reported in the literature (Hicks et al., 1990; Van Koevering et al., 1995; Tatum et al., 2012). Gain to feed ratio (G:F) was numerically greater for the CON groups fed 84 and 102 d, compared to the RIC steers. Performance of steers in the current study was consistent with cattle of similar age and type (Andreini et al., 2020; Parsons et al., 2020).

Carcass data summarized by DOF is shown in Table 4.4. Combining both groups, HCW ranged from 314 to 449 kg, with a mean and SD of 373 ± 25 kg. This was less than the average steer HCW of 390 kg that was reported in the 2016 National Beef Quality Audit (NCBA, 2017). Back fat thickness and EBF percent were similar between groups, with overall means ranging from1.54 to 1.62 cm and 30.0 to 32.2%, respectively. Average industry carcass BF ranges from 1.2 to 1.40 cm (Boudrant et al., 2016; NCBA 2017). Despite a lighter HCW compared to the mean HCW reported by NCBA (2017), carcasses in the current study were 3% fatter than the industry average. In the current study 100% of carcasses graded USDA Choice or greater, but RIC steers had a greater percent of upper two-thirds Choice carcasses compared to CON. Mean and SD in YG was 3.4 ± 0.3, which is slightly greater than the industry average of 3.1 (NCBA, 2017). The positive relationships observed between EBF percent, QG, and YG are consistent with the literature (Garrett and Hinman, 1971; Fox and Black, 1984; Tatum et al., 2006).

Growth curves. Results from the growth model were summarized by RIC and CON sort group. Shrunk body weight increased quadratically, with DOF (Fig. 4.3). The shape of the BW growth curve was similar between groups expect for light—BW sort group, which had a substantially lighter final BW and flatter projection curve, which indicates a slower growth rate and lesser ADG for lighter animals. Although these curves appear linear in shape, if they were extended from birth to mature size, they would begin to curve downward in a logistic fashion, which is consistent with previously reported growth curves for beef cattle (Goonewardene et al., 1981). Current growth projections are consistent with Wilken et al. (2015) that reported SBW increased quadratically with longer DOF for similar type cattle.

Model projections for EBF percent and DOF are shown in Figure 4.4. These projections were consistent with previous studies that show body fat increasing with increased DOF (Owens et al., 1995; Van Koevering et al., 1995; Bourdrant et al., 2016). At the end of the simulation (i.e., 200 d), the light-BW group was leaner than the other groups. Despite the RIC steers being the fattest on d 0, at the end of the simulation the heavy-BW and short-DOF sort groups were fatter than the RIC steers. Model projections showed an inverse relationship between ADG and DOF (Fig. 4.5). Average daily gain declined at decreasing rate with longer DOF, expect for RIC steers, for which ADG decreased linearly. The difference in the shape of the ADG for the RIC cattle could be due to use of individual DMI, rather than pen-averages. Previous studies have reported ADG decreases with longer feeding periods (Van Koervering et al., 1995; Wilken et al., 2015). As a steer approaches its mature BW with increased length of feeding ADG decreases which contributes to the flattening of the BW curve with increased DOF.

Since YG and QG were calculated using EBF percent, trajectories are shaped similar to EBF percent curves (Figures 4.6 and 4.7, respectively).

Observed and predicted DMI for RIC steers is shown in Figure 4.8. Dry matter intake was predicted using Eq. 3, a linear regression line of best fit through the observed data, and a Loess smoothing function. Individual steer DMI was highly variable from day-to-day, but DMI generally decreased with longer DOF. Equation 3 overpredicted DMI, which may be because initial BW of the RIC steers were significantly greater than initial BW reported by Hicks et al. (1990). Dry matter intake predicted using the line of best fit was biologically unlikely, as DMI quickly decreased with DOF, falling below 5 kg per day by the end of the simulation. Dry matter intake predicted using a Loess smoothing function still decreased with increased DOF but with a more conservative approach. The variability among different DMI predictions highlights the need for additional data from cattle fed for an extended number of DOF.

Dry matter intake curves by sort group are shown in Figure 4.9. Regardless of sort group, observed intake curves were characterized by periods of increasing intake followed by sharp decreases in intake, and subsequent steady increases. Generally, within sort group the shape of observed DMI curves were similar, but the timing of intake fluctuations differed by several days. In general, for both individual steers and group fed steers, DMI decreased with increasing DOF, however the Hicks et al (1990) equation often failed to capture this decrease, especially in the case of the RIC steers. As previously stated, initial BW of steers used Hicks et al. (1990) were much lighter at the beginning and end of the feeding period and ADG was less, which day have contributed to the observed differences. Current results indicate opportunities for updating DMI equations to accurately reflect the dynamic of daily feed intake patterns.

Future research should attempt to investigate causation of daily feed intake variation to help better understand mechanisms controlling daily DMI.

Predictions and observed values for SBW, HCW, EBF percent, YG, and QG on the day of harvest are shown in Table 4.5. The model tended to overpredict SBW and HCW with a RMSE of 4.6 and 8.6 kg, respectively. Compared to SBW, the RMSE was greater for HCW since a standard dressing percent of 62% was assumed for all steers. Model HCW projections could be improved by developing new empirically derived equation for HCW prediction. Final EBF percent estimates by the model were precise (RMSE = 0.73). The RMSE for YG was 0.44. As carcasses get fatter and move from a YG 3 to 4, this margin of error may dramatically affect profitability. Further investigation of equations to predict YG and EBF percent using live body measurements is needed. Quality grade was underpredicted with a RMSE of 1.6. Performance of the adapted equation (Eq. 5) could be due to parameter fitting, and adjustments may be able to improve predictability. However, this QG prediction equation from (Fox and Black, 1984) likely needs updating, as relationships between QG and EBF% were based on cattle from the 1970s and since that time cattle height-to-weight ratios have significantly changed (Buskirk, 2020). At the time of harvest, the model predicted well, but growth predictions after the point of harvest cannot be validated.

Table 4.6 shows the predicted optimal harvest day, BW at harvest, and average profit per steer by group. Based on model projections, all groups should have been fed significantly longer. The optimal harvest day in the 200-d simulation ranged from 153 to 196 d. These recommendations were nearly twice as long as the current feeding period. Final harvest SBW for the short- and long-DOF sort groups were 707 and 734 kg, respectively. Final harvest SBW for light- and heavy-BW sort groups was 637 and 715 kg, respectively. Roughage intake control steers were projected for the earliest at 153 d at a SBW of 697 kg. These results suggest BW is a poor indicator of optimal harvest time. Average profit per steer by group is shown in Figure 4.10. Despite other groups having greater projected SBW at harvest, profit per steer was greatest for the RIC group compared to sorted CON groups. Bourdrant et al. (2016) used the same harvest criteria (i.e., observation of 1.27 cm BF), and fed steers for 22 and 44 d past their target harvest endpoint. Similar to the current study, it was reported the greatest revenue was achieved with feeding cattle 44 days past optimal harvest day based on BF thickness. Similarly, Wilken et al. (2015) reported the greatest profitability was achieved when feeding 125% past their expected endpoint. Results of these studies and the current analysis suggest cattle are largely underfished and economic performance is compromised.

Sorting strategy. The effects of sorting by BW and DOF on performance and within pen variability (i.e., SD) is shown in Table 4.7. There were no differences in mean initial SBW (P = 0.95), but as expected due to sorting criterion, variation in initial SBW was significantly reduced (P < 0.01) for the BW sort group. There was no difference in mean initial EBF percent (P = 0.28), but variation in initial EBF percent was reduced for the DOF group, though it was not significant (P = 0.54). However, the lack of significance for initial EBF percent variance is not unexpected since cattle were grouped by expected DOF, not EBF percent. As harvest time was based on body weight, mean final SBW did not differ between sort groups (P = 0.54), but variance in final SBW was significantly less (P < 0.01) for the group sorted by BW. This was unexpected, it was hypothesized that the DOF group would have less variation in final SBW. However, these observed results could be because DOF cattle were not harvested on their optimal marketing day. Mean final EBF percent was the same between groups (*P* = 0.41), but EBF percent variance was reduced for DOF sorted pens, although it was not significant (*P* = 0.40). There were no differences in ADG or GF between BW and DOF groups. In a similar study Sainz and Oltjen (1994) reported means for BW and ADG were not different for steers sorted by BW and predicted DOF determined using the DGM, but the variability in BW and ADG were significantly reduced for the DOF sorted group. In the current study, mean DMI was the same between groups, and there was a tendency (*P* = 0.05) for reduced variation in DMI for BW sorted cattle. However, the tendency for the reduced variation in intake by BW could be due to reduced day-to-day fluctuations in intake by BW steers (Fig.4.9).

The effect of sorting strategy on carcass traits is shown in Table 4.8. There were no differences in mean HCW, YG, BF, REA, or marbling score (*P* > 0.10). Variation in YG, BF, and marbling score were numerically reduced for the DOF group; however, it was not statistically significant (*P* > 0.10). Results from Sainz and Oltjen (1994) suggest significant decreases in carcass trait variation when cattle were sorted by expected DOF. Previous studies have demonstrated sorting by BW can significantly decrease variation in carcass characteristics (Smith et al., 1988; Adams et al., 2010; Hilscher et al., 2015). The cattle in this study were purchased from a single lot and were relatively uniform at the time of sorting, which may have contributed to the similar performance achieved when sorting by BW and DOF.

Average profit per steer was $ 321.42 and $ 235.05 for DOF and BW sorted groups, respectively. Sorting by DOF increased profitability by 26% by increasing harvest BW, improving uniformity, and decreasing overweight carcasses. Although based on comparisons of carcass characteristics at harvest there was no significant reduction in variability among DOF sorted steers, when simulation results were used to compare characteristics on the optimal day of harvest, DOF sorted carcasses were more uniform. Pyatt et al. (2005) compared sorting by HCW, YG and the greatest profit endpoint determined using regression and reported sorting by greatest profit improved profit by thirty dollars per animal. However, implementing modeling techniques to determine the optimal day of marketing requires measurements of individual animal BW, height, and body fatness upon entering the feedlot. Garcia et al. (2005) evaluated large scale implementation of sorting by expected DOF based on measurements taken at initial processing and reported sorting by DOF increased profitability and decreased carcass weight variation by 18% as compared to unsorted controls.

Different grid prices and feed costs will impact marketing optimums and sorting strategy. When selling on a grid-basis like in the current study, cattle should be fed longer to maximize HCW (Streeter et al., 2012; Boudrant et al., 2016). With a high Choice-Select spread, the additional weight and increased QG can overcome the discounts from overweight carcasses and YG 4 and 5 (Fuez, 2002; Wilken et al., 2012). As seen in the current study, when base prices were relatively high, it was advantageous to feed animals longer to achieve heavier carcass weights. A large-scale commercial feedlot evaluation of pen by Tatum et al. (2012) showed the greatest returns were achieved with cattle that were lighter at feedlot placement and fed a longer number of days. Harvest optimums widely varied among pens based on intake and growth patterns, and harvesting cattle based on “rule of thumb” marketing estimates decreased profitability. Profitability estimates for the CON sort group highlights individual animals do not need to be sold at their optimum to improve profitability, net returns can be increased by increasing weight and reducing YG and weight discounts (Pyatt et al., 2005).

Results from the growth models and economic analysis showed that cattle needed to be fed substantially longer to reach their marketing optimum. However, in the current study feed costs were relatively low, and increasing feed costs would decrease optimal DOF. Feeding and carcass performance of the cattle in the current study were consistent with industry averages for this type of breed and feeding system. Despite BF and EBF percent being above the recommended harvest targets, the authors still feel the cattle were under finished, based on the predicted marketing optimums and the actual HCW and YG at the time harvest. These findings suggest there are inconsistencies between estimates of body fatness and equations used to evaluate YG and QG. As HCW have steadily increased in the past decades (Peel, 2021), it is reasonable to assume REA has also increased, and relationships between carcass weight and fat have changed. Projections using equations 4 and 5, yields underpredictions for YG and QG. When using the commonly suggested target BF (i.e., 1.1 cm) with heavier carcasses, YG is decreased. In a similar vein, data from the current study suggests an EBF of 28.6% is sufficient to grade low choice, warranting a need to update the relationship between EBF percent and QG.

IMPLICATIONS AND CONCLUSIONS

Results of the current study suggest growth curves can be used to simulate the performance and profitability of individual steers to pinpoint harvest optimums. Body weight, YG, and QG all increase with increased DOF, but marketing optimums vary based on grid prices and feed costs. Current recommendations for body fatness at harvest may be too low. Although the cattle in the current study were of acceptable finish, harvesting them too early decreased profitability. Sorting cattle using the DGM to determine expected DOF was more profitable than sorting by BW. Future studies should examine the effects of body composition, growth, and dry matter intake over extended feeding periods to expand the range of data available for growth prediction models. By using real time BW, body composition, and DMI to develop growth projection models, advanced machine learning algorithms can be used to accurately sell cattle at their optimums.

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FIGURES

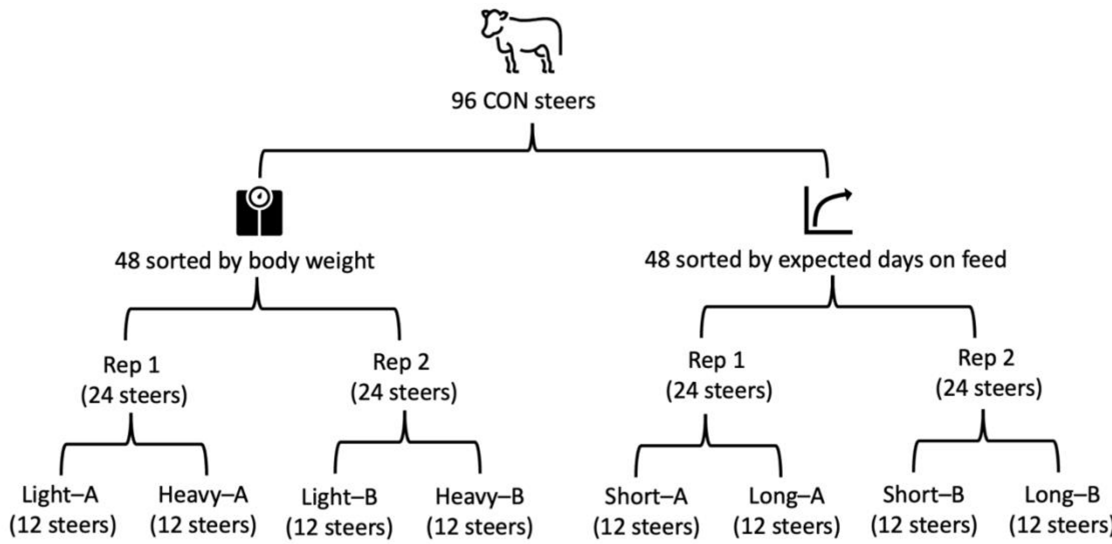

Figure 4.1. Configuration of sort treatments for conventional (CON) steers

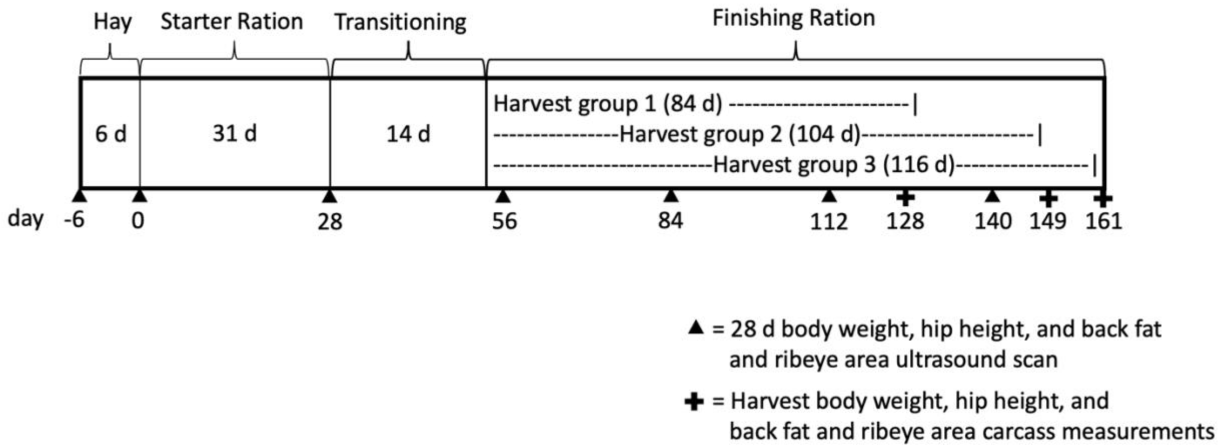

Figure 4.2. Project timeline

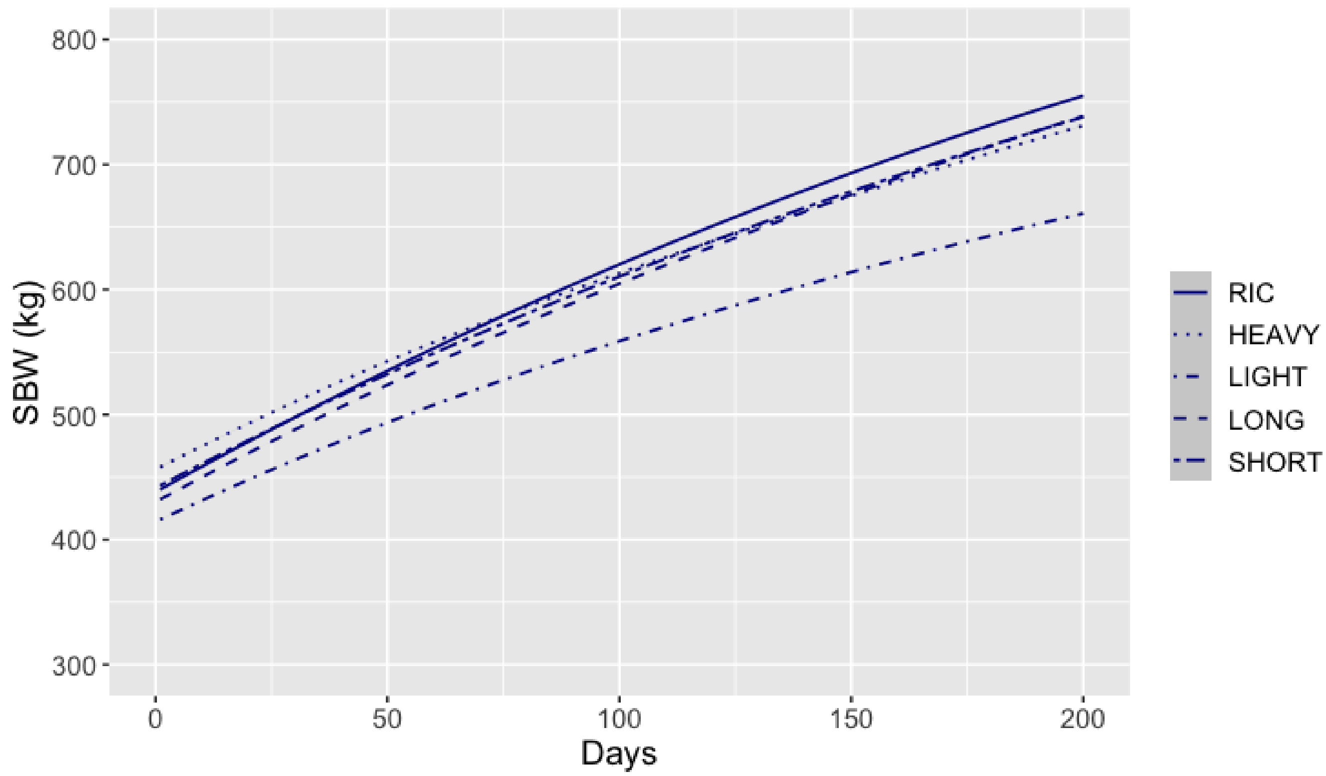

Figure 4.3. Model projections for shrunk body weight (SBW) for individually fed roughage intake control (RIC) and conventional steers by sort group

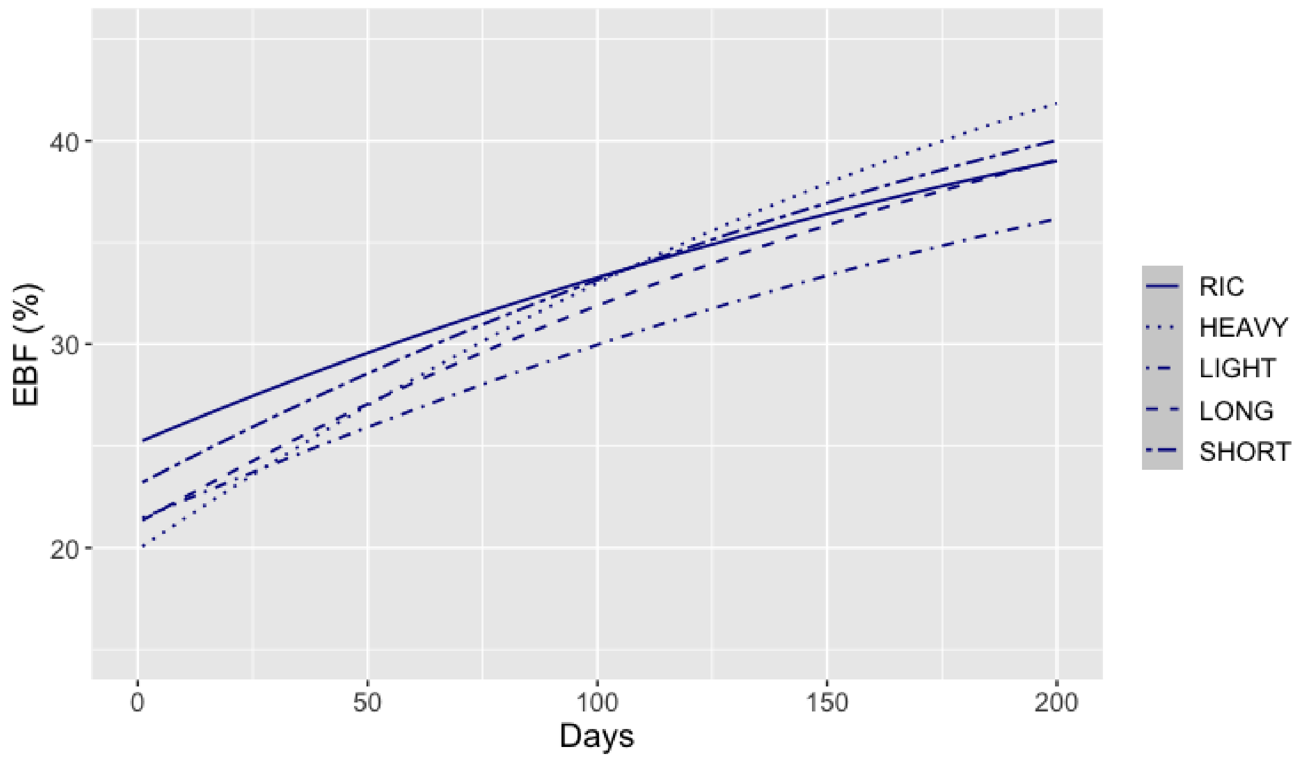

Figure 4.4. Model projections for empty body fat (EBF) percent for individually fed roughage intake control (RIC) and conventional steers by sort group

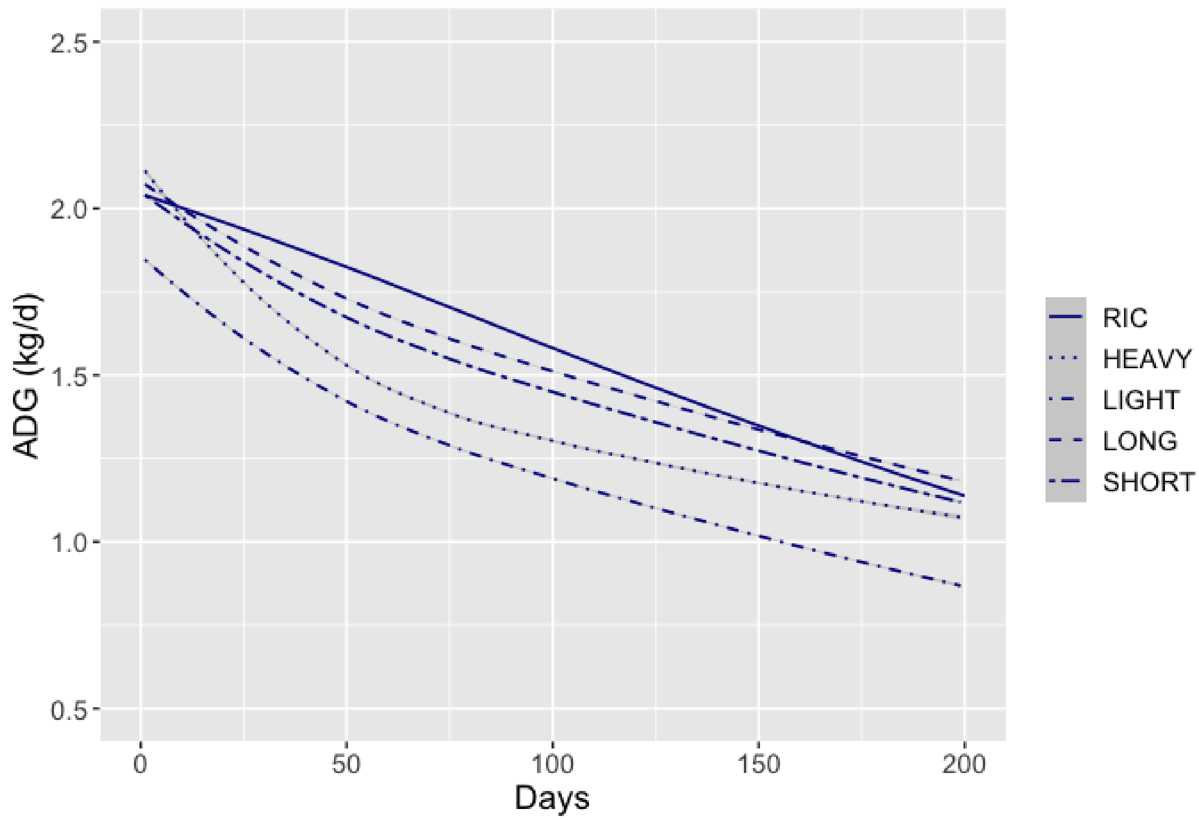

Figure 4.5. Model projections for average daily gain (ADG) for individually fed roughage intake control (RIC) and conventional steers by sort group

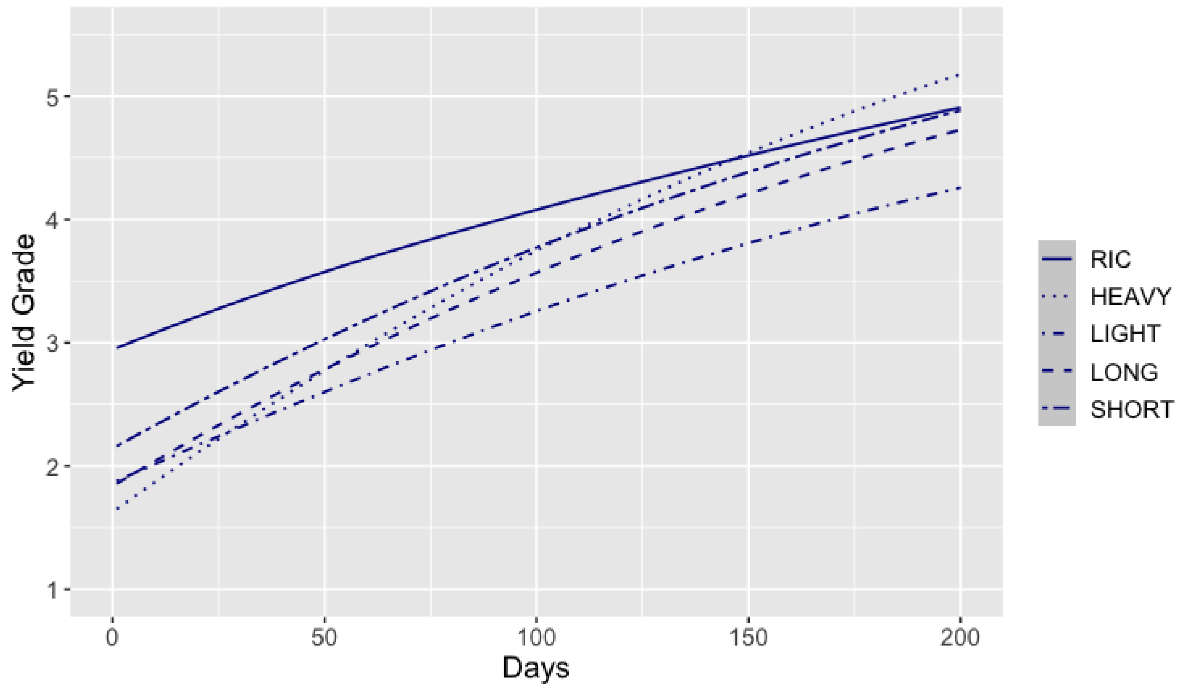

Figure 4.6. Model projections for Yield Grade (YG) for individually fed roughage intake control (RIC) and conventional steers by sort group

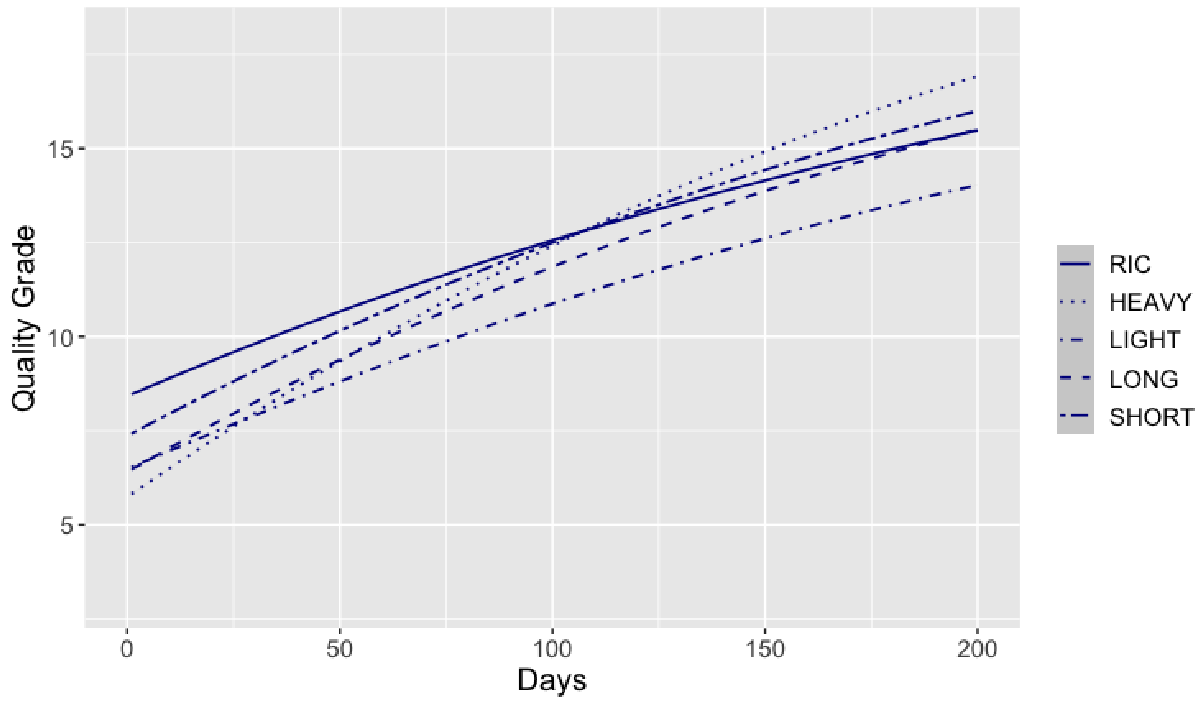

Figure 4.7. Model projections for Quality Grade (QG) for individually fed roughage intake control (RIC) and conventional steers by sort group

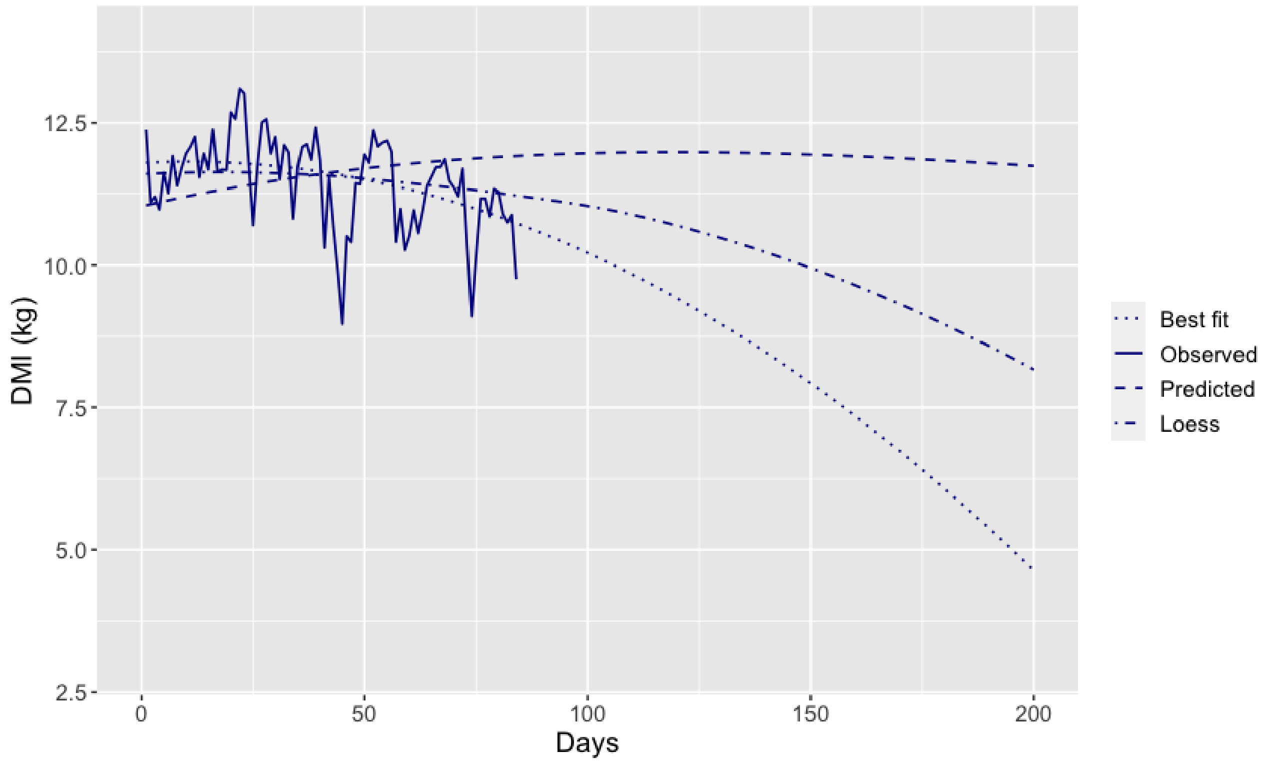

Figure 4.8. Observed and dry matter intake (DMI) predicted using Hicks et al. (1990), a quadratic line of best fit, and a Loess smoothing function for steers individually fed a high concentrate ration using a roughage intake control system

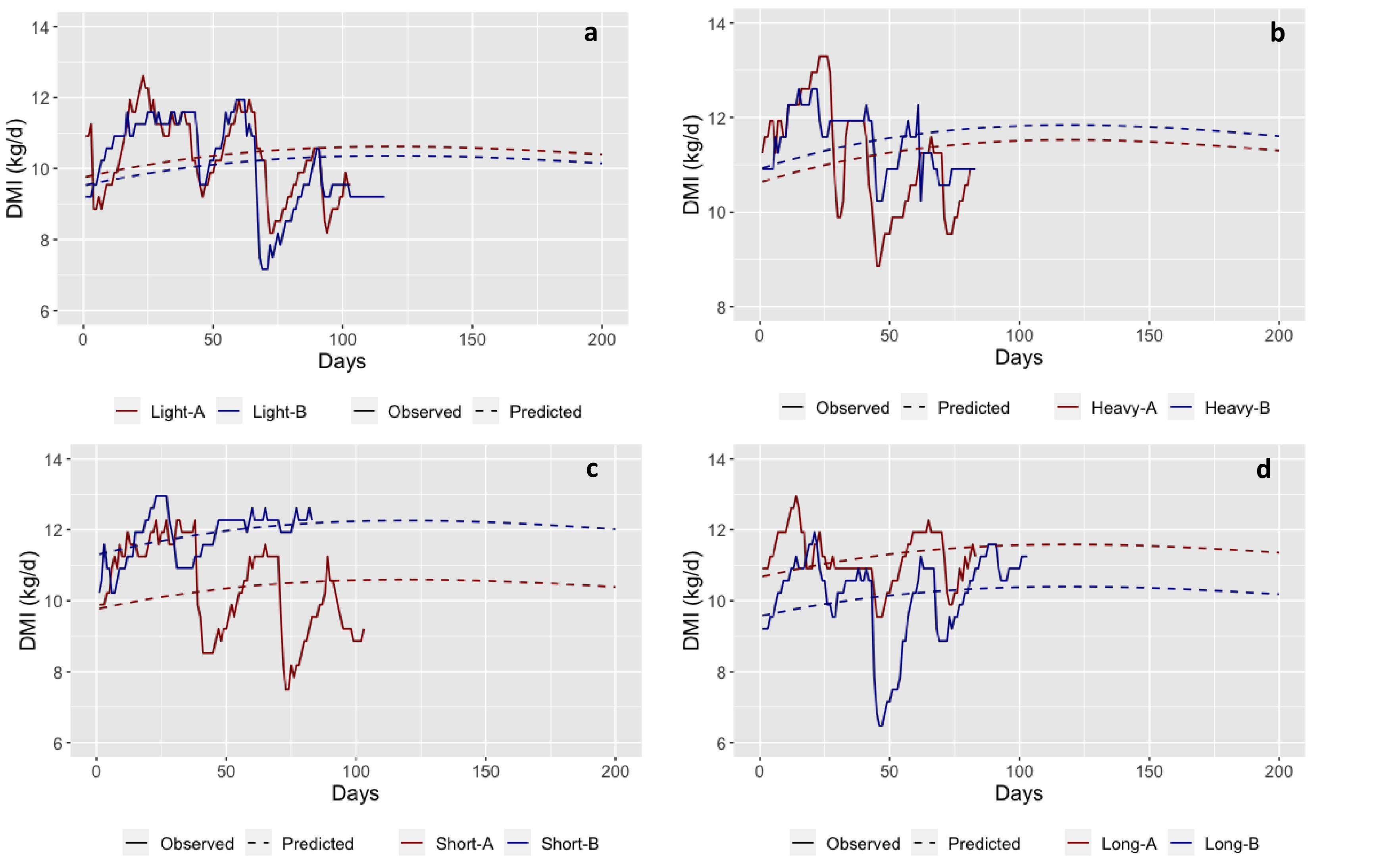

Figure 4.9. Observed and dry matter intake predicted using Hicks et al. (1990) for steers fed a high concentrate diet and sorted by either body weight (light and heavy) or days on feed (short and long), **a)** Light—body weighted sorted pens, **b)** Heavy—body weighted sorted pens, **c)** Short—days on feed sorted pens, and **d)** Long—days on feed sorted pens

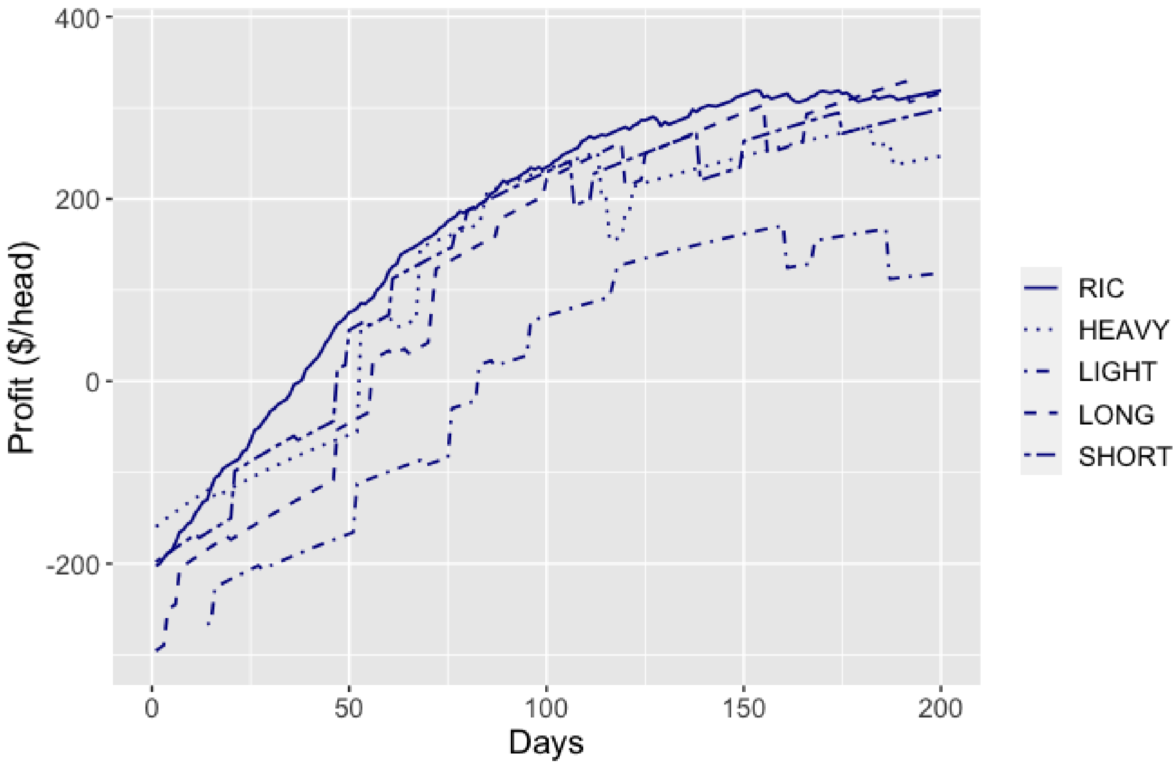

Figure 4.10. Model projections for profit for individually fed roughage intake control (RIC) and conventional steers by sort group

TABLES

Table 4.1. Ration composition on a percent *dry matter basis*

Parameter	Starter	Transitioning	Finisher
Rolled Corn, %	41.99	51.12	72.00
Dried distillers grains, %	20.00	20.00	6.00
Wheat hay, %	15.00	8.00	6.00
Alfalfa hay, %	12.00	10.00	5.00
Yellow grease, %	1.50	2.00	3.00
Molasses, %	8.00	7.00	3.00
Urea, %	0.35	0.40	1.80
Beef trace salt, %	0.32	0.32	1.00
Rumensin, %	0.02	0.02	0.02
Calcium carbonate, %	0.82	1.15	1.80
Magnesium oxide, %	0.32	0.00	0.02
Potassium chloride, %	0.00	0.00	0.50
Ration energy, Mcal/ kg DM			
Maintenance net energy	1.88	1.98	2.02
Gain net energy	1.24	1.33	1.38

Table 4.2. Carcass prices used in the economic analysis

Attribute	Price, \$ 45.4/kg carcass weight[1]
Carcass base price	200.00
Yield Grade Premium/Discounts	
1	4.00
2	2.00
3	0.00
4	−11.75
5	−16.60
Quality Grade Premium/Discounts	
Prime	10.00
Certified Angus Beef	4.00
Choice	0.00
Select	−10.00
Carcass Weight Premium/Discounts	
Carcasses > 413 kg	−5.00
Carcasses > 433 kg	−15.00

[1]Prices were obtained from USDA (2019a,b)

Table 4.3. Means (± SD) for performance traits by days on feed for steers fed a high-concentrate diet individually in a roughage intake control system (RIC) and conventional feed bunks (CON)

Parameter	RIC 84 d	CON 84 d	CON 102 d	CON 116 d
N =	24	48	36	12
Initial shrunk body weight, kg	438 (12)	445 (28)	426(31)	414 (19)
Final shrunk body weight, kg	598 (26)	603 (40)	605 (45)	605 (36)
Dry matter. intake, kg	11.6 (0.9)	11.4 (0.1)	10.2 (0.3)	10.0 (*na*)
Average daily gain, kg	1.92 (0.26)	1.91 (0.30)	1.71 (0.26)	1.64 (0.26)
Gain:Feed	0.166 (0.02)	0.175 (0.01)	0.169 (0.01)	0.163 (*na*)

Table 4.4. Means (± SD) for carcass traits by day on feed for steers fed a high-concentrate diet individually in a roughage intake control system (RIC) and conventional feed bunks (CON)

Parameter	RIC 84 d	CON 84 d	CON 102 d	CON 116 d
Hot carcass weight, kg	367 (20)	373 (21)	378 (29)	372 (24)
Marbling[1]	576 (79)	560 (94)	568 (94)	579 (93)
Ribeye area, cm sq.	88.3 (5.6)	91.5 (6.9)	92.2 (6.2)	89.8 (5.4)
Back fat thickness, cm	1.62 (0.30)	1.61 (0.36)	1.54 (0.32)	1.67 (0.41)
Initial empty body fat, %	25.9 (1.8)	19.9 (2.1)	24.1 (2.2)	19.4 (3.1)
Final empty body fat, %	32.2 (2.2)	31.2 (2.7)	31.3 (2.9)	30.0 (2.6)
Yield Grade	3.5 (0.5)	3.3 (0.7)	3.2 (0.6)	3.1 (0.73)
Upper 2/3 choice and greater, %	91.7	83.3	82.8	75.0

[1]Marbling score (slight^{00} = 300, small^{00} = 400, modest^{00} = 500, etc.)

Table 4.5. Observed and model predicted values for characteristics at harvest combining steers fed a high-concentrate diet individually in a roughage intake control system (RIC) and conventional feed bunks (CON)

Parameter	Observed	Expected	Root mean square error
Shrunk boy weight at harvest, kg	600	604	4.61
Hot carcass weight, kg	370	373	8.55
Final empty body fat, %	31.5	31.1	0.73
Yield Grade	3.3	3.5	0.44
Quality Grade[1]	12.3	11.6	1.64

[1] Quality grade: Standard: < 9.5, Select: 9.5 to 10.5, Low Choice 10.5 to 11.5, Mid Choice: 11.5 to 12.5, High Choice: 12.5 to 13.5 and ≥ 13.5 Prime.

Table 4.6. Optimal marketing day and average profit for steers fed a high-concentrate diet individually in a roughage intake control system (RIC) and conventional feed bunks (CON) by sort group

Group	Optimal day	Shrunk body weight at harvest, kg	Profit, $/steer
Roughage intake control	153	697	319.14
Light–body weight sort	173	637	187.59
Heavy—body weight sort	185	715	282.51
Short–days on feed sort	187	707	307.45
Long–days on feed sort	196	734	335.38

T**able 4.7**. Effects of sorting by body weight (BW) and expected days on feed (DOF) on performance

Parameter	Means				Variance			
	BW	DOF	SE	P-value	BW	DOF	SE	P-value
Initial shrunk body weight, kg	433	435	14.90	0.949	20.9	30.6	1.36	0.036
Initial shrunk body weight, kg	602	606	3.82	0.542	48	35	0.85	0.008
Initial empty body fat, %	22.2	20.2	0.78	0.275	3.0	2.6	0.38	0.536
Final empty body fat, %	31.5	30.6	0.57	0.409	2.94	2.41	0.36	0.401
Average daily gain, kg/d	1.77	1.85	0.07	0.489	0.26	0.32	0.03	0.382
Dry matter intake, kg/d	10.3	10.5	0.43	0.826	0.18	0.65	0.08	0.054
Gain:Feed	0.17	0.18	0.005	0.442	0.009	0.001	0.005	0.448

Table 4.8. Effect of sorting by body weight (BW) and expected days on feed (DOF) on carcass performance

Parameter	Means				Variance			
	BW	DOF	SE	*P*-value	BW	DOF	SE	*P*-value
Hot carcass weight, kg	371	377	3.24	0.321	21.2	30.2	0.45	0.005
Yield Grade	3.09	3.34	0.088	0.191	0.677	0.637	0.091	0.788
Back fat thickness, cm	1.56	1.62	0.047	0.443	0.38	0.33	0.029	0.355
Ribeye area, sq cm	90.9	92.2	0.788	0.379	6.16	6.74	0.907	0.697
Marbling score[1]	564	568	17.5	0.871	96.3	88.3	7.36	0.522

[1]Marbling score (slight^{00} = 300, small^{00} = 400, modest^{00} = 500, etc.)