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Evaluation of Herd Size Management Strategies

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Evaluation of Herd Size Management Strategies

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science in Agricultural Economics

by

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University of Arkansas
Bachelor of Science in Agriculture, Food and Life Sciences, 2017

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This thesis is approved for recommendation to the Graduate Council.

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Abstract

This thesis is comprised of two studies examining the effects of price signal based herd size management strategies on profitability of cow-calf operations. Herd size management strategies were evaluated across the previous two cattle cycles, 1990-2014, using a fixed land resource and included a variety of production scenarios. These scenarios varied in terms of stocking rates, fertilizer applications rates, and calving season. Each scenario was also analyzed both with and without weather effects on forage production. Weather effects were simulated using a production index derived from satellite imagery across the observed 25-year period. Three herd size management strategies: i) constant herd size; ii) dollar cost averaging; and iii) price signal-based, anticipatory counter-cyclical expansion/contraction, were evaluated on the basis of net present value of cash operating profits as well as on the basis of risk in terms of range of yearly cash operating profit. This analysis revealed fall calving herds with increased forage production and hay sales through medium fertilizer application in conjunction with a counter-cyclical herd size strategy to be the profit-maximizing management choice regardless of inclusion/exclusion of weather effects or time period. However, a constant herd size strategy was shown to create little regret in terms of net present value of cash operating profit. The second study attempts to rank causal variables that drive the differences in profitability across herd size strategies as well as land use intensities revealed in the first study. Two techniques, linear regression and artificial neural networks (ANNs), were compared and contrasted on the basis of relative variable impact rankings as well as goodness-of-fit. This analysis showed cattle price and head sold to be the largest drivers of profitability across the study period. In addition, fall calving was reinforced as the profit-maximizing decision while optimal choices regarding fertilizer application and stocking rate were not apparent. While ANNs were shown to be

superior in terms of goodness-of-fit, linear regression provided coefficients, which allowed for more meaningful examination of tradeoffs between calving seasons, stocking rates, and fertilizer rates.

Acknowledgements

I would like to first thank my advisor, Dr. Michael Popp, for his continued support, enthusiasm, and guidance throughout my undergraduate and graduate research. Accomplishing my academic goals in a compressed time frame would not have been possible without Dr. Popp's encouragement and countless hours of assistance. I would also like to thank my committee, Dr. Bruce Dixon and Dr. Lanier Nalley, for their valuable research assistance. Additionally, I would like to thank Dr. Nathan Kemper and Mr. Grant West for their contributions to this research and publication.

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List of Published Papers

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Chapter I. Introduction

A. Problem Statement and Study Justification

Many cattle producers are aware of the cattle price cycle, but often accept price fluctuations as an unavoidable reality of cattle production. In cow-calf production specifically, producers often respond to low prices by contracting herd size by either selling breeding stock or more commonly, retaining fewer heifers. This strategy helps stabilize cash flows and appears to be logical given the expectation of continued low prices in the short-term. Additionally, this producer behavior perpetuates the cycle. As producers retain fewer heifers and reduce herd size, markets are inundated with supply and prices continue to fall until the resulting smaller breeding stock is unable to meet demand. This reduced supply, over time, thus results in prices beginning to rise and a new cycle is started.

The nature of the cattle cycle and observation of producer behavior raises questions about a counter-cyclical strategy that attempts to capitalize on the high prices experienced during a cycle while mitigating cash flow risk during the low price period of the cycle. Little research has been dedicated to answering this question, especially under real-world conditions experienced by producers. Land and forage constraints are a reality for many producers such that expansion and contraction of herd size leads to either excess hay production or the need to purchase hay. Additionally, weather risk as it pertains to forage growth is an important factor in cow-calf production that is almost impossible to forecast or predict. Using the Forage and Cattle Planner (FORCAP) tool, counter-cyclical herd size management (HSM) strategies were examined under simulated production risk and spring and fall calving seasons across the 1990-2003 and 2004-2014 cattle cycles. In addition to examining HSM strategies across multiple cycles and calving seasons, several levels of fertilizer use were evaluated where added forage

production was either sold or stocking rate of cattle was increased resulting in three scenarios with different land-use intensities (LUI) entailing use of fertilizer and stocking rate.

Comparisons of HSM strategies across multiple cycles as well as manipulating calving seasons and LUI's enhanced the ability to generalize results from this research. This analysis made a unique contribution to research involving cow-calf herd management strategies and provided useful insights to producers interested in increasing profitability through implementation of a price-based HSM strategy.

The analysis mentioned above yielded extensive data on simulated cow-herd performance statistics that spanned 25 years for a variety of HSM \times LUI strategies. While profitability differences between HSM strategies were analyzed, the driving factors behind the profitability differences were not identified in Chapter II. Hence, two modeling techniques, standard multiple linear regression and artificial neural network analyses were compared and contrasted to determine which of cattle price, number of cattle sold, hay price, number of hay bales bought or sold, calving season, weather, and fertilizer use had the largest impact on cow herd profitability.

B. Objectives

Chapter II analyzes the profitability of cow-calf HSM strategies across the previous two cattle cycles under forage production risk from weather effects, by calving season, and LUI. Weather effects were captured using an index developed from satellite imagery. The null hypothesis was that price-signal based HSM strategies have the same level and risk of annual cash operating profits as a cow-calf operation were the breeding herd size was held constant.

Chapter III compares and contrasts two modeling techniques in an attempt to rank the impact of explanatory variables on cow-calf profitability. Predictive performance was evaluated across the two previous cattle cycles, separately, and across the entire period. The null hypothesis was that rankings of the impacts of explanatory variables are the same across modeling technique. A second null hypothesis was that the goodness-of-fit (R^2) of the modeling techniques does not vary by modeling technique.

C. Overview of Methods

The analysis presented in Chapter II was made possible by utilizing the FORCAP tool (available at <http://agribusiness.uark.edu/decision-support-software.php#forcap>). To perform the analysis needed for this research, the tool was modified to include price data from 1990 forward. Also, FORCAP was modified to model weather risk by using a weather index to adjust monthly forage production. Varying forage production drives hay and corn feeding needs of the herd during winter months or for periods when forage production on pastures is insufficient during the growing season to meet herd nutrition requirements. Hay and corn feeding impact production cost and thereby profitability of the cow herd. In total, 1,800 individual model runs resulted in cow herd performance statistics that could be compared by HSM, calving season, cattle cycle, and LUI. Multiple linear regression and artificial neural networks (ANNs) were used to compare and contrast their goodness-of-fit and to rank the impact of explanatory variables on annual cash operating profitability. Chapter III was written in a manner that assumes the reader has some familiarity with the function and application of ANNs. A literature review of ANNs, presented next, sheds some light on important aspects of different ANN modeling techniques deemed relevant for Chapter III's analysis.

D. Review of Artificial Neural Networks

ANNs are a method of machine learning that mimics the function of the human brain with the purpose of determining complex relationships within data (Palisade, 2015). In biological neural networks, neurons are capable of sending and receiving information from many other neurons. This manner of interconnection is also the foundation of ANNs. This analytical technique is capable of identifying relationships and trends within data that are not apparent using traditional statistical analysis tools. The algorithms used in ANNs are not fixed and rigid to one problem as many traditional statistical techniques are. ANNs utilize flexible algorithms that are self-organizing in a manner that makes them useful for solving non-linear or non-stationary problems (Graupe, 2007). The flexibility of ANNs extends to data that are both categorical and numeric in form for both explanatory and dependent variables. In an ANN, connections between explanatory variables can be seen as neurons, which are the foundation of ANNs.

The algorithm behind the network is tasked with exploring varieties of connections between the variables or neurons. The algorithm tests both varying combinations of connections as well as varying weights on those connections. In biology, connections between neurons are not equal in that some connections take priority over others. Additionally, some connections inhibit transmission while others promote transmission of information. Artificial neural networks are designed in much the same manner. As in the biological model, some connections are modeled as inhibitory, meaning that they decrease the impact on the outcome or dependent variable, while other connections are weighted as excitatory, meaning they increase the impact on the dependent variable (Olden and Jackson, 2002). This flexibility and exploratory aspect is the driver behind ANN's capability to identify complex relationships and patterns. To identify these relationships the network must be "trained" on a portion of the input data that is randomly picked

from observations. Hence, with different model runs, different solutions are attained that ideally converge on similar outcomes. The fact that different solutions are obtained from multiple analyses on an identical data set as a result of the random nature of selecting training observations is distinctively different from regression analysis.

Training involves iteratively changing the weights or patterns placed upon variables to find the combination that minimizes the sum of squared errors. This approach opens the door to settling on a local minimum and not on the global minimum in applications using weights instead of patterns. Artificial neural networks mitigate this problem by starting with large weight changes and reducing them slowly in an effort to hone in on the global minimum. This process is the driver behind the long processing time associated with ANNs. Compared to many other computer driven analysis methods, ANNs require significantly more time to analyze data (Graupe, 2007).

After a network has been trained, the next step is to “test” the network. To test a network, the portion of the input data that was not used during training is predicted based upon the neural net developed during training. Known explanatory variable values are used as input for the trained net to make predictions. These predicted values are then compared to the actual value to test the accuracy and predictive capacity of the ANN within sample. Typically, the training and testing process is performed several times as the user can stipulate different percentages of the initial data set to use. As such, trained neural networks can be compared to showcase the accuracy and consistency of predictions (Palisade, 2015) using several different approaches described next.

Since their inception in the 1950’s, ANNs have grown rapidly and spread through many fields of research. As such, they have taken on a variety of forms or configurations that tailor the

network to certain problems (Graupe, 2007). This review focuses on three modeling configurations; multi-layer feed forward networks, probabilistic neural networks, and generalized regression neural networks, that are referenced in Chapter III.

1. Multi-layer Feed-forward Networks

Multi-layer Feed Forward (MLF) Neural Networks are a type of supervised training process that work through back propagation (Svozil, Kvasnicka, & Pospichal, 1997). Supervised networks are networks in which the desired output or dependent variable value is known and the network adjusts connection weights between explanatory variables and nodes in a hidden layer as well as those nodes and the explanatory variable to achieve the configuration that yields the closest approximation or best outcome prediction. Backpropagation is a method for examining the effect that weights have upon the output function. By taking the partial derivative of the output function with respect to the connection weights, the network can determine how changing a weight affects the output value. This enables the network to manipulate the weights to move towards the known desired output value and, therefore, minimize the sum of squared errors. The name “backpropagation” stems from the fact that the process begins with the error term of the output value and then examines weights backward throughout the network to find the source of the error and then minimize it (Nielsen, 2018). This backpropagation occurs throughout the foundation of MLF networks, which are layers. In MLF configurations, there is the input layer, the output layer, and a varying number of hidden layers (Figures 1.1 & 1.2). These hidden layers are comprised of nodes that are used to define the relationships between inputs and outputs. In MLF networks, all nodes from one layer are connected to every node in the forward layer. Each connection is then assigned an associated weight. Palisade’s (2015) Neural Tools® uses one hidden layer and a choice of 2 to 6 nodes.

2. *Probabilistic Neural Networks*

Probabilistic Neural Networks (PNN) are structured in somewhat the same way as MLF networks, but their function is significantly different. As shown in Figure 1.3, PNNs are designed with four layers: input, pattern, summation, and output (Specht, 1990). The input and output layers function in the same way as MLF networks, but the divergence occurs in the two hidden layers. Pattern layers are designed to use each input and apply a set pattern to that input. Each pattern unit represents a pattern gathered from one observation of the training data. These patterns are then grouped into categories that are designated using the Bayes Strategy for Pattern Classification. The Bayes Strategy utilizes probability distribution functions (PDFs) to define categories that minimize the expected risk of making a poor prediction. Probability density functions can be estimated using a small set of training data although larger data sets serve to minimize expected error (Specht, 1990). Pattern units calculate the conditional probability of the given inputs fitting well into that specific pattern which was observed in the previous training data (Kubat, 2017). Once the probability of fit is calculated, it is sent to the summation unit where probabilities from all pattern units are evaluated and the best choice for that set of input data is selected. The output value is a category specification that results from the chosen pattern and its associated category based upon the Bayes Strategy (Specht, 1990). Categories are comprised of patterns with the highest probability of fit or minimum expected error. Because PDFs can be estimated from a small data set, PNNs are able to classify data faster than backpropagation techniques such as MLF networks. Additionally, because patterns and pattern classifications are learned and defined within the system, new inputs can be quickly analyzed and categorized when compared to back propagation techniques which require retraining of the network. Numerical outcome prediction using PNN are organized in the same manner.

3. *Generalized Regression Neural Networks*

Generalized regression neural networks (GRNN) are a subset of (PNNs) and similarly require much less training data when compared to MLF networks. All training data values contribute to every prediction, but those observations closest to the desired output value are given more predictive power (Figures 1.4 & 1.5) using a smoothness parameter. From this property, the network gathers its explanatory power. A smoothness parameter of one implies that all training values are weighted equally regardless of distance from the desired value. Therefore, a small smoothness parameter implies that training values with explanatory values in close proximity to those of the predicted value are weighted higher than those farther away (Figure 1.4). Whereas MLF networks require very large data sets to obtain a prediction through backpropagation, a GRNN is able to make predictions with fewer training values by utilizing input from all training points and manipulating the smoothness parameter to minimize the sum of squared errors (University of Wisconsin, nd; Specht, 1991).

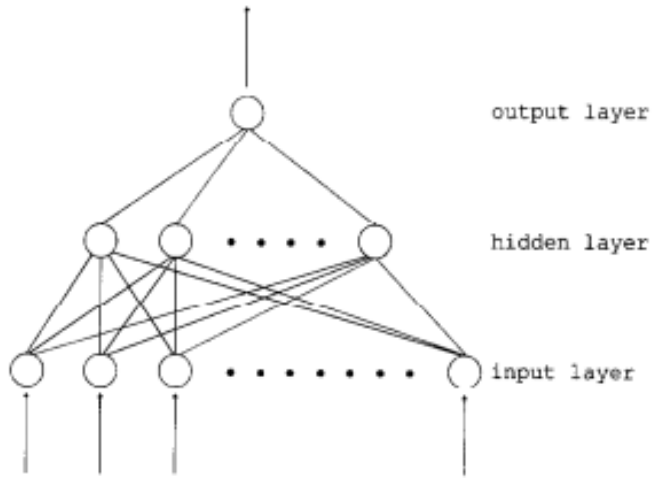
D. Overview of Chapters

Chapter II details a 25-year analysis of three HSM strategies utilizing fall and spring calving herds with and without weather effects by calving season and LUI. Chapter III builds on Chapter II by describing the relative impact of explanatory variables on the profitability differences using two different modeling frameworks. Chapter IV concludes by summarizing findings and suggests areas for future research.

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F. Tables and Figures



Source: Svozil, Kvasnicka, & Pospichal, 1997.

Figure 1.1. Diagram of Feed-forward Neural Network with One Hidden Layer

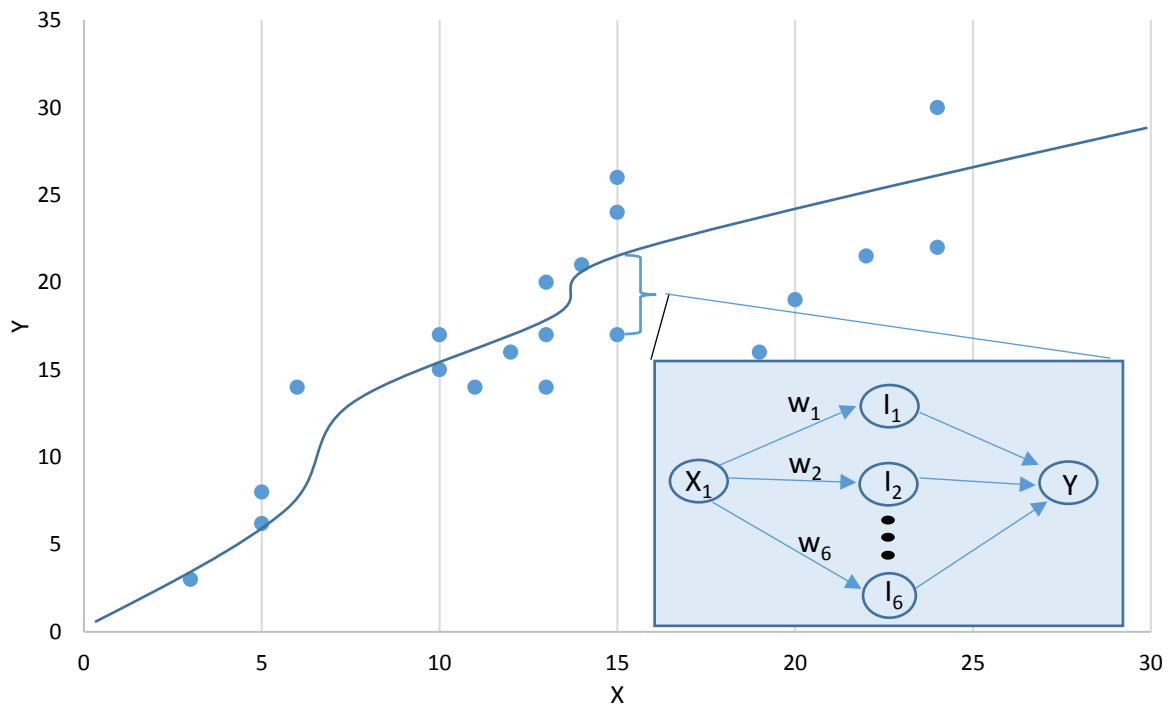
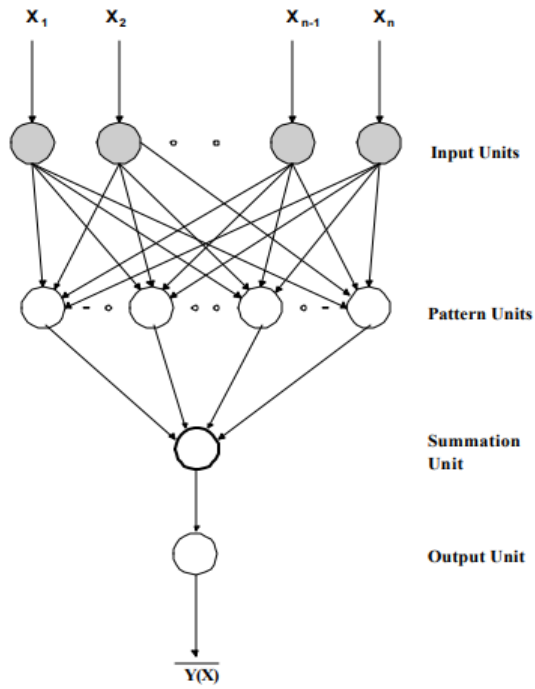


Figure 1.2. Multi-layer Feedforward Neural Network Diagram



Source: University of Wisconsin, nd

Figure 1.3. Diagram of a Probabilistic Neural Network

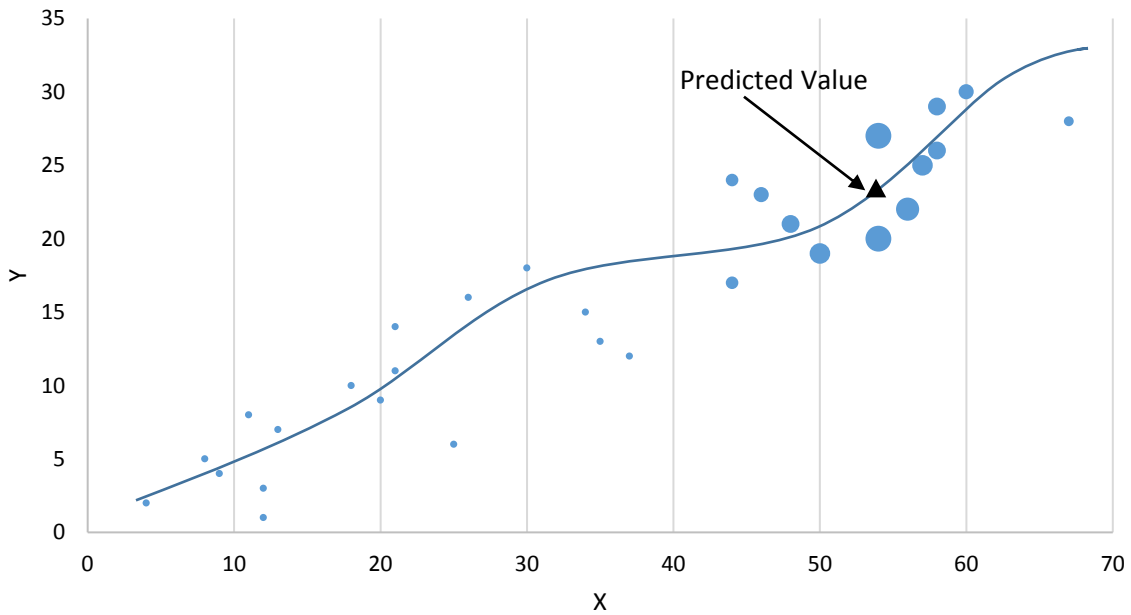
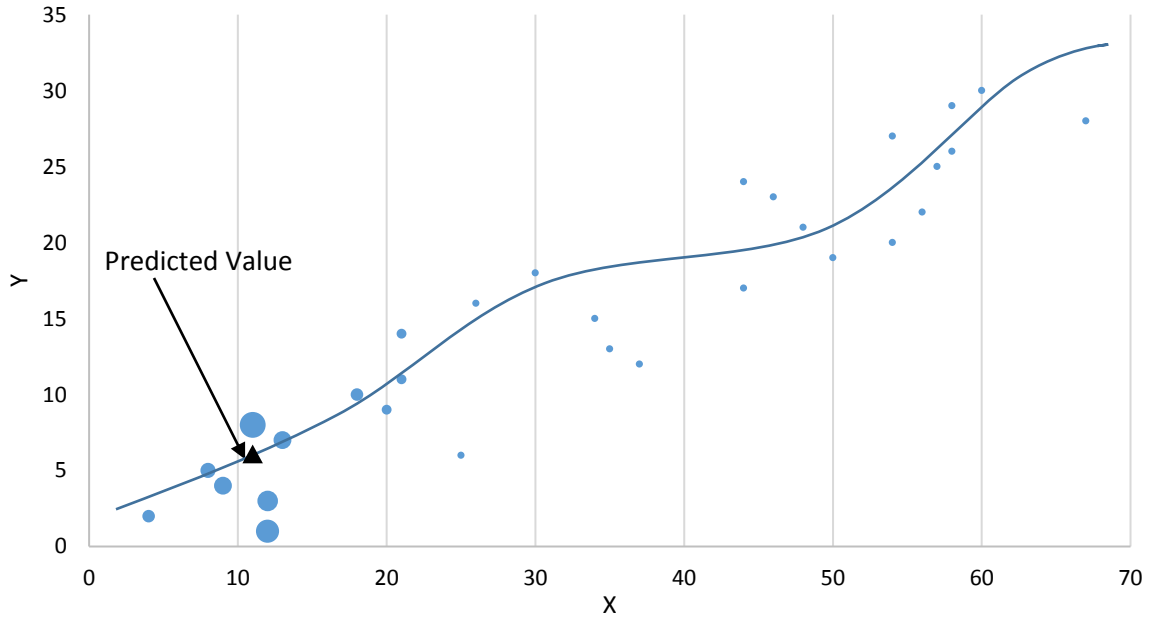


Figure 1.4. Generalized Regression Neural Network Diagram with Low Smoothness Parameter

Note: Dot size represents contribution to predicted value. Therefore larger dots represent training observations with higher contributions to predictions closer in proximity to the level of X at the prediction (\blacktriangle) while smaller dots represent those observations that contribute relatively less. Weighting is a function of horizontal distance between observations and a particular predicted outcome's X value.

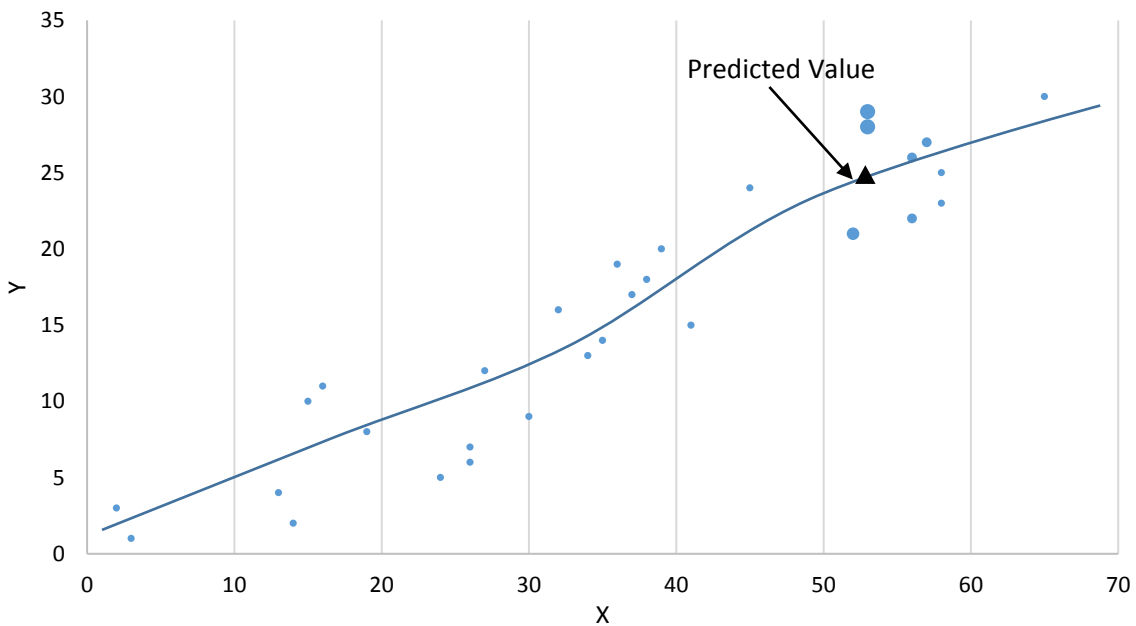
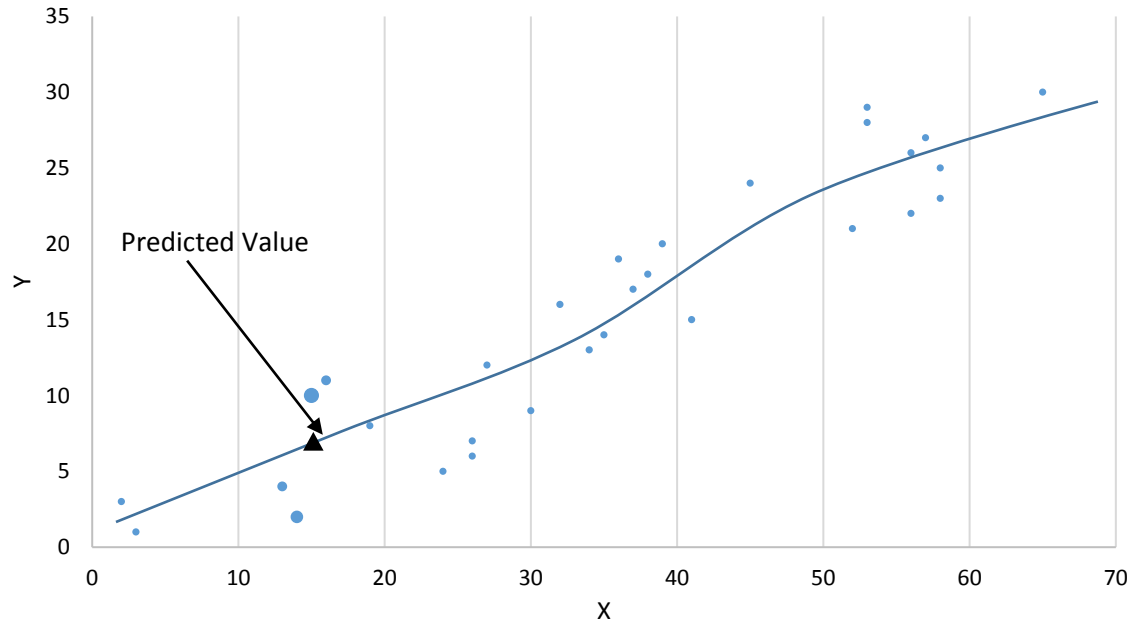


Figure 1.5. Generalized Regression Neural Network Diagram with High Smoothness Parameter

Note: Dot size represents contribution to predicted value. Therefore larger dots represent training observations with higher contributions to predictions closer in proximity to the level of X at the prediction (\blacktriangle) while smaller dots represent those observations that contribute relatively less. Weighting is a function of horizontal distance between observations and a particular predicted outcome's X value.

Chapter II. Impact of Weather and Herd Size Management on Beef Cow Profitability

A. Introduction

Cattle production is an important industry to agriculture in many U.S. states as aggregate U.S. agricultural commodity cash receipts in 2015 totaled \$78.2 billion with cattle and calf sales contributing 21% of that total (NASS 2016). Changes in the U.S. herd size, attributed to weather (specifically drought), macro-economic factors, and varying cattle and feed prices, can have large economic repercussions for the livestock sector. For example, with the expanded use of corn for ethanol production over the course of the last twenty years, U.S. corn prices eventually increased enough to make it the most valuable commodity in terms of total production value rather than cattle and calves in 2005 (Park and Fortenberry, 2007). The national drought in 2011-12 led to large-scale herd liquidation resulting in subsequent, record cattle prices for 2012-2015. These record cattle prices, in turn, caused the eventual rebuilding of the U.S. herd to end the 2004-2014 cattle cycle.

The average cattle cycle, defined as the time span between sequential inventory lows, typically lasts from 8 to 12 years (Matthews et al., 1999) as a function of i) beef export/import conditions with fluctuating exchange rates, disease outbreaks and/or trade restrictions; ii) cattle and feed prices; iii) weather events; iv) producer credit constraints (Bierlen et al. 1998); and, v) a biological production lag where an added heifer retained at 7 months of age and bred at 15 months of age leads to an extra calf born and finished as early as 36 months after the retained heifer was born. Hence, national herd expansion is slow compared to possible contraction via the slaughter of mature cows (Hughes, 1987). Furthermore, Hamilton and Kastens (2000) show that, in addition to the exogenous factors mentioned above, market timing attempts by producers are a significant determinant of cattle price cycles. Also, cow-calf production occurs mainly on

pastures and encompasses a majority of the time needed from birth to slaughter. Pasturing cattle is characterized by production uncertainty due to drought, flooding, fires, and snow events that affect cost of production to a larger extent than confined animal feeding conditions for competing meat products of pork and poultry (Matthews et al., 1999). As such, exogenous factors such as weather introduce uncertain forage production. Rosen (1987) proposes that producers capitalize on these factors by selling (retaining) calves when the exogenous shock results in an increase (decrease) in the market price, thus perpetuating the price cycle.

Careful planning and flexibility to manage these price cycles by way of herd size expansion/reduction and/or on-farm forage production and acquisition of supplemental feed is required to maintain adequate cash flow, to manage income tax repercussions, and to manage price and production risks (Hughes, 2000). Further, the larger a producer's herd size, the larger the potential financial implications. The average U.S. cow-calf operation has approximately 40 head (Jones, 2017), and operations of this size or smaller are often non-intensive labor enterprises on small parcels of grassland providing a source of supplemental income. Operations of less than 100 head encompass 91% of operations but represent less than half of the total cattle inventory (USDA ERS, 2016). On the other hand, operations with over 100 head account for 51% of U.S. cattle inventories, while only 9% of total operations (Jones, 2017). It is this latter size category where herd size management begins to play a more noticeable role on profitability in dollar terms rather than rates of return to resources employed when compared to smaller operations.

Generally, producers expand herd size when prices and producers' returns are high resulting in an increased beef supply several years later (Bentley and Shumway, 1981). However, with expansion of beef supply comes the inevitable decline in prices, and hence, the decision to

expand the herd in years past, was potentially counterproductive. Expanding the herd when prices are high and liquidating when prices turn low is contrary to the old adage of “buy low, sell high” and thus it may be beneficial for producers to counter-cyclically expand production when prices are low and decrease herd size when prices are high (Griffith et al., 2017). Along the same line, Hamilton and Kastens (2000) show that a counter-cyclical strategy outperforms constant herd size and cyclical strategies over a 25 year period. Thus a herd size management strategy that anticipates future price trends is encouraged (Bentley and Shumway, 1981; Trapp, 1986; and Lawrence, 2002) as herd size management strategies that react to price signals can lead to greater returns when compared to strategies that assume constant herd sizes. In that regard, Lawrence (2002), compared a constant herd size (CHS) strategy to i) a strategy where sales receipts from heifer sales are constant and thereby more/fewer heifers are sold during low/high price years, respectively; and ii) a dollar cost averaging (DCA) strategy where replacement heifer reinvestment is held constant by again changing the number of heifers retained with changing cattle prices (selling more/fewer when prices are high/low). Lawrence (2002) encouraged the DCA strategy. However, weather effects were excluded and extra land resources were rented when needed and assumed to be available. A study by Lutes and Popp (2015), showed the impacts of weather to increase ten-year income risk under both constant and changing herd size scenarios when land resources are held constant. Herd size changes followed state cattle inventory changes reflecting average producer choices. They used a cow/calf simulation tool, the Forage and Cattle Planner (FORCAP) and analyzed the effect of alternative grazing methods and associated stocking rates (Popp et al., 2014).

Using FORCAP, the objective of this research was to examine cow/calf cash operating profitability with a fixed land resource and three herd size management strategies both with, and

without weather effects over the course of the last two cattle cycles. Since cow-calf operations can modify calving season and amount of fertilizer use, we compare CHS and DCA herd size management strategies along with a strategy based on moving average prices (MA). The MA strategy involves the use of a price ratio of a short- to a longer-run moving average to signal an up- or downtrend in cattle prices, thereby allowing an anticipatory countercyclical herd expansion/contraction reaction to profit from price changes. Results quantify to what extent profit-maximizing, long-term calving season, fertilizer use, and herd size management strategy choices are affected by i) simulated weather effects on forage production generated using satellite imagery; and, ii) time period or cattle cycle analyzed.

B. Materials and Methods

1. FORCAP

The Forage and Cattle Planner (FORCAP), (available at <http://agribusiness.uark.edu/decision-support-software.php#forcap>) is a decision tool that allows comparison of a plethora of different cattle production practices, using either default or operation-specific production parameters, by summarizing profitability and production efficiency changes in an automated spreadsheet application.¹ Smith et al. (2016) used the tool in an optimization framework, but this was not possible for this work as the multi-year framework to analyze cattle cycles required hundreds of annual FORCAP model runs. Farm size, as measured by stocking rate and land use (dedicated to pasture or hay production), is a key parameter as are calving season, use of fertilizer inputs, and forage production as affected by weather. Cash operating profits (π) are estimated annually and result from sale of cattle and excess hay after accounting for feed and supplements, seed, fuel, fertilizer, twine, chemicals, medication, vaccines, veterinary services, operating interest, repairs, and maintenance as shown for a sample year in Table 2.1. Different

calving seasons lead to changes in exposure to fescue toxicity and thereby a lower breeding failure rate with fall calving than spring calving (Caldwell et al., 2013). Hence, fewer head of calves were sold with spring calving at seasonally lower annual calf and cull cattle prices as reflected in the lower gross receipts and lower direct costs associated with lesser sales when compared to fall calving. Forage production uncertainty as highlighted in Figure 2.1 and evident in feeding statistics in Tables 2.2 and 2.3, led to monthly changes in forage production that in turn affected hay production and supplemental feed needs given herd nutrition requirements that are impacted by cow gestation and lactation needs estimated from month to month. Noticeable for 2004 was the need for purchased hay given less than expected forage production throughout the year except July (Figure 2.1), which translated to a need for purchased hay as most major forage production months were impacted negatively and more so under spring calving conditions in that year. By the same token, supplemental feeding of corn during the winter months was higher with fall calving than spring calving as nutritional needs of the cows peak in the winter months when lactating to support calves that were born in fall.

Capital ownership charges including depreciation, insurance, property taxes and opportunity cost of capital are excluded as land, equipment, and building resources used did not change across production practices discussed next. The exception is a set of model runs involving a higher stocking rate that did require added capital investment in breeding stock. Ramifications of these added capital recovery charges and property taxes are discussed below.

2. *Land Use Intensity*

For each of the three herd size management strategies (CHS, DCA, and MA), three levels of fertilizer application rates are analyzed to showcase the impact of varying cattle and hay output on profitability while holding pasture and hay land constant over time (Table 2.4).

Further, these nine herd size strategy × land use intensity combinations are analyzed i) by calving season (fall vs. spring); ii) with and without weather effects on forage and attendant hay production; and, iii) over two cattle cycles.

As summarized in Table 2.4, land use intensity is increased from left to right by increasing fertilizer application that translates to greater forage production in the middle column and greater stocking rate in the right most column. Least fertilizer use yields a small hay surplus that is indicative of an operation that relies mainly on cattle revenue for income. Adding fertilizer on pasture allows greater opportunity to harvest excess hay from pasture and diversifies revenue streams given added hay sales. Adding even more fertilizer increases forage production sufficiently to allow a higher cattle stocking rate with hay sales similar to the least fertilizer outcome. Forage productivity with different fertilizer application rates is uncertain, however, as weather impacts production and thereby hay and corn feeding results. While the impact of weather uncertainty on supplemental feed and hay sale information is highlighted in Tables 2.1-2.3 for least fertilizer use. Greater fertilizer use amplifies weather effects on forage production as discussed next.

3. *Production Index*

Monthly forage production is tracked historically using imagery and associated NDVI (Normalized Difference Vegetation Index) data collected by LANDSAT. LANDSAT typically reports two NDVI values per month for a specific location (30 m spatial resolution). Chosen for this analysis were six pasture/hayland areas in Washington County in Northwest Arkansas as the researchers were familiar with the history of those fields from casual observation over time. The fields were also identified using historical cropland data layer data available through NASS (National Agricultural Statistics Service, 2017) as far back as 2008, to have at least partial

assurance that the fields were in pasture or hayland production throughout the analyzed period, 1990-2014. Therefore, twelve NDVI values per month (two each for six locations), except for some missing observations with data collection problems like cloud cover, for example, were available to create a time-varying vegetation index that would lend itself to capture weather impacts on forage production.² To capture changes in forage production, the ratio of an individual month's average NDVI value for all six fields for a given year to its twenty five-year average (1990-2014) for a particular month indicated deviations from long-term conditions observed for each month. Note that these fields likely had different forage species mixes over time but those trends are not discernable from either the crop data layer or satellite imagery. Hence, average NDVI values of six fields were used to remove variability in forage species crop mix that might occur on a single field. These ratios were further divided by the average of the examined period ratio values to create a production index that would average to 100% over the period as follows:

$$(2.1) \quad RPI_{ij} = \frac{NDVI_{ij}}{\left(\frac{\sum_j NDVI_{ij}}{25}\right)} \quad \forall \quad i = \text{Jan.} - \text{Dec.} \text{ and } \forall j = 1990 - 2014$$

$$(2.2) \quad PI_{ijk} = \frac{RPI_{ijk}}{\left(\frac{\sum_{jk} RPI_{ijk}}{Y_k}\right)} \quad \forall \quad i = \text{Jan.} - \text{Dec.}, \text{ and } \begin{cases} \forall j_k = 1990 - 2003 \text{ where } Y_k = 14, \text{ or} \\ \forall j_k = 2004 - 2014 \text{ where } Y_k = 11, \text{ or} \\ \forall j_k = 1990 - 2014 \text{ where } Y_k = 25 \end{cases}$$

where *RPI* is the raw production index, NDVI is the six-field average for a particular month *i* in year *j*, and *PI* is the standardized production index that varies by production period, *Y_k*.

A *PI* value above (below) one indicates a relatively productive (poor) forage production month, respectively. Multiplying *PI* by average monthly forage production as a percent of total

annual yield, weather induced impacts on forage production could be estimated. Note that increased fertilizer application leads to increased monthly forage production that in turn is affected by the production index for simulation of weather effects. The monthly default distribution of forage production used in FORCAP (Tables 2.2 and 2.3) is based on expert opinion of John Jennings (2013) and Charles West (2013) and is similar to values found in Gadberry (2015) and Huneycutt et al. (1988). Adding weather effects by using the production index, a modification to FORCAP, impacted grazing capacity and attendant need to supplement herd nutrition requirements with hay and corn as shown in Tables 2.2 and 2.3 for 2004 as an example. In turn, hay sales or purchases were a result of on-farm hay production on both hay land and pastures and the amount of hay fed to the herd. Weather effects on ability to harvest hay (e.g. excessively wet conditions could preempt harvest) were not addressed.

Monthly variability in the forage *PI* values by select years from 1990-2014 are shown in Figure 1 to demonstrate how forage production was impacted on a monthly basis. As mentioned earlier, 2012 was a drought year that impacted summer forage availability nationwide and also on the fields analyzed here. However, early spring and late fall conditions for forage production were above average in 2012. Forage production in 2004, by contrast, only had one above average forage *PI* value in July. Figure 2.1 thus demonstrates the amount of risk cow-calf producers face in terms of forage and hay availability with direct implications for cow-calf profitability as FORCAP automatically supplements with hay and corn when nutrition requirements are not met by forages growing on pasture.

Prices, in part driven by supply uncertainties and time of transaction in a particular year, were modeled at the state level and annual time step given data availability for hay, corn, fertilizer, fertilizer application costs, seed cost for winter annuals, and diesel fuel for 1990-2014

(Figure 2.2). For fertilizer and fuel prices, data was gathered from NASS (2014) for 1990-2008 and from Mississippi State University (2014) for 2009-2014. Hay and feed prices were collected from NASS (2014). When data was not readily available for these inputs, similar inputs with available price data, were used to estimate a value for that year (Tester, 2017).

4. *Baseline Model Parameters*

For each level of fertilizer use, a baseline set of parameters was used to resemble a fall- or spring calving, Arkansas cow-calf operation. This baseline used 80 acres of hay land and 320 acres of pasture that was rotationally grazed to allow the producer to harvest excess forage from pasture when available. Additionally, 80 acres of winter wheat were sod seeded yearly on pasture in the fall for graze out in spring months to model forage production of winter annuals in FORCAP. Fertilizer application is varied and described in Table 4. As is common in Northwest Arkansas, pasture forage species consisted of 25% Bermuda grass, 65% fescue, and 10% clover by area. Hay forage species consisted of 50% Bermuda grass, 45% fescue, and 5% clover by area. Forage production for a species was thus calculated as acres in production multiplied by annual grazing potential of a pure stand of the species. This calculation was then adjusted by month for seasonal forage availability and was further adjusted by weather effects if desired. FORCAP defaults were used for mature/young cow weights, birth weight, weaning weight, and age. When necessary, FORCAP calculates supplemental feed needs in the form of corn and hay to ensure adequate crude protein and total digestible nutrient intake for maintaining cow body condition. The fall calving season, where calves are born in October, was selected to enhance breeding success compared to spring calving, where calves are born in April and fescue toxicosis leads to a greater likelihood of breeding failure (Caldwell et al., 2013). One herd sire is utilized for every thirty cows. Therefore, for the two observed cattle cycles, 100 cow herd operations

with least or intermediate fertilizer use required four herd sires while highest fertilizer use with 160 cows required six herd sires. Over the cattle cycle, five revenue streams were available annually and included the sale of: i) weaned steer calves; ii) weaned heifer calves; iii) cull cows; iv) cull herd sires; and v) excess hay produced on farm.

5. *Herd Sire and Calving Management*

All 100-cow scenarios began with a herd consisting of 83 mature cows and 17 young cows that were exposed to the herd sires each year and 18 replacement heifers needed for herd replenishment given one cow death loss. All 160-cow scenarios, began with a herd consisting of 133 mature cows, 27 young cows, and 29 replacement heifers to allow for two cow death losses. Average Arkansas prices, as reported by USDA AMS, were used each year and adjusted for seasonal differences in prices between fall and spring calving herds. All cows and heifers were assumed to be bred in January and July of each year for the fall and spring calving herds, respectively. Heifers were bred at 15 months of age to calve for the first time at 24 months of age. Culling and heifer retention decisions were made in May and November of each year, for fall and spring calving herds, respectively, and occurred at the same time calves were weaned and sold. One sixth of the breeding herd was culled yearly based upon the expectation of weaning six calves from a cow over their useful lives. Cows that were open as a result of breeding failure were also culled. The FORCAP default rate of six and twenty percent breeding failures, for fall and spring calving herds, respectively, along with one and three percent death losses for cows and calves, respectively, were used (Smith et al., 2012; Ritchie and Anderson, 1994). The number of replacement heifers needed to maintain the herd size was thus a result of cull cows sold either due to age or for being open and cow death losses. FORCAP v.2 2014 was modified to allow retention numbers to be manipulated by the user to grow or shrink the herd

from year to year. A separate model run was performed each year, by herd size management strategy, fertilizer application rate, calving season, and inclusion or exclusion of weather effects. A total of 1,800 annual herd performance measures were collected which included cash operating profit, hay sold, and head sold as estimated in FORCAP.

6. *Herd Size Changes across Strategies*

The CHS strategy simulates a producer who maintains a constant herd size despite changing weather and cattle prices as hay and corn are considered available for purchase as needed. This strategy is considered the least management intensive.

For the countercyclical MA strategy, the simulation assumes the same starting herd size as the CHS strategy. However, herd size subsequently grows or declines given heifer retention decisions that are based on the price ratio of 10- to 27-month moving average steer prices at the time of breeding each year (January and July, for fall & spring calving herds, respectively). A price ratio above one, signals the sale of added heifer calves to reduce herd size in anticipation of eventual downward pressure on prices when otherwise retained heifers would lead to added weaned calf sales. A price ratio below one, signals herd expansion in anticipation of an eventual upward trend in prices. For both signals, two or three additional heifers, pending 100- or 160-cow herd size, respectively, are sold or added in comparison to maintaining the herd at the size of the prior year. Prices for steers were used for signals, as they make up the majority of cattle sales (Table 2.1). The 27-month period was chosen as a second rebreeding of retained heifers would occur at that time and the shorter-term, 10-month period, captures the time period from the start of breeding to calving with an average one-month period for breeding. Using a larger increment or decrement for extra heifers to retain was not undertaken in this study as herd sire needs would change over time.

The constant dollar reinvestment DCA strategy uses constant yearly reinvestment in the herd. Producer heifer retention reactions to market conditions are simulated by using nominal prices. Yearly herd reinvestment was determined by finding the value of an 800 pound heifer in the herd size adjustment or calf sale month (Eq. 2.3) and multiplying by the number of replacement heifers needed based on herd size (Eq. 2.4). These annual reinvestment values were then averaged across cycles (1990-2003 and 2004-2014) to find the target constant yearly average dollar reinvestment (Eq. 2.5) needed to determine the annual number of replacement heifers to retain given that year's replacement heifer value (Eq. 2.6) as follows:

$$(2.3) \quad PRH_{js} = PH_{js} \cdot 8 \quad j = 1990 - 2014 \text{ and } \begin{cases} s = \text{May} \forall \text{ fall calving herds} \\ s = \text{November} \forall \text{ spring calving herds} \end{cases}$$

$$(2.4) \quad R_{jst} = PRH_{js} \cdot \begin{cases} l = 18 \forall 100\text{-cow scenarios} \\ l = 29 \forall 160\text{-cow scenarios} \end{cases}$$

$$(2.5) \quad \overline{R_{slk}} = \sum_{jk} R_{jst} / Y_k \quad \begin{cases} \forall jk = 1990 - 2003 \text{ where } Y_k = 14, \text{ or} \\ \forall jk = 2004 - 2014 \text{ where } Y_k = 11 \end{cases}$$

$$(2.6) \quad QRH_{jstlk} = \overline{R_{slk}} / PRH_{js} \text{ rounded to the nearest head}$$

where j again represents a year in the cattle cycle, PRH_{js} is the yearly value of an 800 pound replacement heifer in \$/head by calving season, s , PH_{js} is the annual price in \$/cwt of a 7-800 pound heifer, R_{jst} represents the value of replacement heifers given l head of replacement heifer needs associated with cow herd sizes of 100- or 160-cows, $\overline{R_{slk}}$ is the average yearly reinvestment that depends on calving season, herd size over the analyzed period, k , and QRH_{jstlk} is the annual number of heifers retained by year, calving season, land use intensity, and period analyzed. For the 25-year analysis, the same herd sizes as in each cycle were used except for 2003 when heifer retention returned the herd to 100 or 160 cows for the start of the second cycle.

7. *Analysis*

Cash operating profit risk over time was analyzed using box and whisker plots for each herd size management strategy for each level of land use intensity, with and without simulated weather effects, by calving season, and for each cattle cycle or time period. Rather than developing a model that selects the optimal producer choice in terms of cash operating profit, given an array of risk aversion levels, the reader is thus expected to visually assess the inherent risk differences across the management options presented.

Aside from annual cash operating profits, the number of bales of hay and cattle sold, provided insight about the primary sources of revenue for a herd size management strategy \times land use intensity combination. Hay and head sold describe performance implications of management choices in terms of physical production units rather than dollar terms.

Finally, profits were examined using the minimum regret rule. Regret was calculated using net present value (NPV) of annual cash operating profits across the entire cattle cycle(s) to account for inflation and risk. Regret is defined as the loss a producer would incur over the course of a cattle cycle(s) as a result of choosing a sub-optimal herd size management strategy for a particular level of land use intensity. Regret was calculated for each cattle cycle(s), with and without simulated weather effects, and by calving season and was termed HSM regret. Regret numbers thus quantify differences across the herd size management options evaluated. These regret numbers easily allow for assessment of consistency of herd size management strategy choice across periods analyzed and/or whether simulated weather effects were included or not. Also calculated were regret values for the choice of land use intensity pursued within a given herd size management strategy. Again these numbers were calculated by cattle cycle(s) and weather effects combinations and were termed LUI regret. NPV was calculated using a

nominal discount rate of 8% (Hardie, 1984) that reflects common, agricultural lending rates over the period analyzed.³

C. Results

Described below are herd size changes as a function of the chosen herd size management strategy followed by a discussion on attendant profitability and risk implications by calving season in order of cattle cycle(s). Effects of weather on risk and profitability are discussed throughout.

1. Herd Size Fluctuations

Breeding herd size changes over time for operations starting with 100 cows are shown in Figure 2.3. For the 1990-2003 cycle, the MA strategy had the largest herd in 1998, while the DCA strategy peaked at a higher level in 1997 and led to greatest total cattle output when compared to the other two herd size management strategies. During this cycle, the lowest cattle prices were encountered in 1996 (Figure 2.2) and led to noticeably rapid herd size expansion for the DCA strategy in particular. In comparison to the CHS strategy, both the MA and DCA strategies had larger overall average herd sizes when cattle prices were on the rise (Figures 2.2 and 2.3).

For the second cattle cycle, the DCA and MA strategies led to more pronounced differences in herd size changes over time (Figure 2.3). The MA strategy led to three years of herd reduction followed by four years of expansion before reverting back to three more years of reduction to end the cycle. The DCA strategy steadily expanded the herd until 2012 when further retention was too costly given high cattle prices.

Since the DCA strategy maintained the largest herd throughout the observed periods, this strategy consistently yielded the lowest hay sold and the highest number of head sold (Tables 2.5 and 2.6). Although achieving the goal of selling more cattle during the period of high cattle prices, lower hay sales and/or greater hay purchases more than offset added cattle revenue.

2. *Fall Calving*

For the 1990-2003 cycle, our results indicated that the addition of weather effects on forage production increased risk in terms of range (max. – min.) of annual cash operating profit (π) regardless of land use intensity or herd size management strategy (Figure 2.4). Additionally, increased land use intensity, decreased profitability regardless of herd size management strategy. This was especially so, since added capital recovery charges of approx. \$3,500 and added property taxes summed to nearly \$3,800 per year. Table 2.5 reflects these costs in the larger breeding herd strategy outcomes with highest land use intensity. According to LUI regret, low land use intensity was the profit-maximizing choice in the first cycle in the absence of weather effects for all herd size management strategies. Once weather effects were included, profit-maximizing land use intensity increased to medium for CHS and MA, whereas for DCA, least fertilizer use was profit-maximizing. With least fertilizer use, including weather effects led to hay purchases on average for the DCA strategy. For all herd size management strategies, hay sales were lower on average and exhibited much larger variation in part because of different cattle output, but also because of changes in forage production when weather effects were included. Choosing, medium land use intensity as profit-maximizing, the MA strategy emerged as the least HSM regret choice regardless of weather effects. Choosing least fertilizer use, the MA strategy was profit-maximizing without weather effects and the DCA strategy was profit-

maximizing when weather was included. Finally, range of π was highest with highest fertilizer use.

During the second cycle, the range in π did not increase with the addition of weather (Figure 2.4) regardless of land use intensity. Nonetheless, the distance from the 25th to 75th percentile observations increased. Given the observation of lesser range in π for the second cycle compared to the first, weather had a lesser effect on income variability. This change in weather effects on income variability was, in part, a function of the period-specific adjustment effects on forage production. As shown in Figure 2.1, forage production index values during winter months, showed forage production to be lower than the long term average in the second cycle whereas forage production was higher than the long term average in the first cycle. In slight contrast to the previous cycle, π increased with greater land use intensity regardless of herd size management strategy as hay prices were high enough to offset heightened input cost by selling excess hay (Figure 2.2). For the management option with greatest fertilizer use and added cattle sales, added cost of fertilizer and added ownership charges for extra breeding herd investment could not be offset except using CHS in the scenario with weather effects. Hence, medium fertilizer use had least LUI regret, and at that level of fertilizer use, NPV of π was highest for MA regardless of weather. Finally, as shown in Figure 4, the most intensive land use management choice showed the greatest range in π .

As expected, results for both cycles, spanning production years 1990-2014, exhibited similar trends as observed across each cycle individually. Range of π increased with the addition of weather, as expected, regardless of herd size management strategy or land use intensity (Figure 2.4). As land use intensity increased, NPV of π increased for the 100-cow herds and subsequently fell for the 160-cow herd (Table 2.5). As such, the medium fertilizer option was

profit-maximizing given zero LUI regret across all herd size management options. Medium land use intensity also exhibited approximately the same level of income risk as the low land use intensity option (Figure 2.4). At that level of fertilizer use, the MA strategy showed least HSM regret regardless of weather (Table 2.5). When taking profit-maximizing land use intensity choice into account for each period of analysis, the addition of weather for the longest run did not impact herd size management strategy choice which was different from the results for the previous two cycles.

Given the objective of examining long term impact of weather and time period on management choices⁴, it was noticeable that the size of HSM regret values over the 25 year period were quite small. Choosing CHS, the least management intensive herd size management option, with medium fertilizer use, for example, and assuming that weather simulation was reasonable, only led to a regret of \$2,840 dollars over 25 years and even less when using least fertilizer. There are differences across cycles as discussed above and adding weather effects increased income risk as uncertain forage production led to changes in sales above and beyond variation caused by changes in cattle prices and number of head sold. Nonetheless, HSM regret values did not consistently increase or decrease when weather effects were added for comparisons within individual land use intensity \times cattle cycle combinations. Under low land use intensity in the first cycle for example, regret increased for the CHS choice when weather was added while it declined for the same cycle with medium fertilizer use. As such, and as might be expected, weather played an uncertain role as to what herd size management strategy to pursue. The same can be said for cattle cycle impacts on herd size management strategy choice.

3. *Spring Calving*

Similar to fall calving, adding weather effects on forage production for spring calving operations increased range in π , as did an increase in stocking rate (Figure 2.5). Also, for the period 1990-2003, the CHS strategy was dominant in terms of HSM regret regardless of land use intensity (Table 2.6) and by more compelling regret amounts in comparison to numbers presented for fall calving in Table 2.5 for the same cycle. Compared to fall calving, increased breeding failure rate led to less income as was already demonstrated for a sample year in Table 2.1. Adding weather uncertainty weakened profitability as hay sales declined along with added variation in forage production (Table 2.6). In contrast with fall calving, hay sales were higher given different seasonal nutrition needs as demonstrated in Tables 2.2 and 2.3 for 2004 as an example. Added hay revenue was insufficient to offset lower cattle revenue given lesser beef production with greater breeding failure rates for spring calving when compared to fall calving. Hence least fertilizer was the profit-maximizing, least LUI regret choice regardless of weather effects inclusion.

Over the second cycle, the CHS strategy was once again profit-maximizing by having least HSM regret values for both low and medium land use intensity. With high fertilizer use, the MA strategy had \$9.81 more NPV than the CHS strategy. Further, in terms of LUI regret, highest profitability was achieved using the medium level of fertilizer use in the second cycle as was the case for fall calving. Hence higher cattle prices in the second cycle did generate sufficient revenue to offset the marginal cost of added fertilizer which also traded at higher prices (Figure 2.2). As with fall calving, the range of π was smaller when weather risk was added in the second cycle. The 25th and 75th percentile range increased but to a lesser extent when compared to fall calving. However, weather effects manifested themselves in a greater range of π and in a more

positively skewed fashion in comparison to fall calving (Figures 2.4 & 2.5). The second cycle proved more profitable than the first cycle given higher cattle and hay prices (Figure 2.2) that were sufficient to offset greater fertilizer, seed, and corn prices.

The 25-year analysis for spring calving led to the same profit-maximizing herd size management strategy, CHS, and again, regardless of land use intensity, or weather effects. Medium fertilizer use was profit-maximizing with least LUI regret. High land use intensity was not justifiable and led to highest income risk (Figure 2.5).

In comparison to fall calving, the optimal herd size management strategy was clearly the CHS strategy as that choice did not vary by cycle or with weather effects. Profit-maximizing fertilizer use was a less obvious choice as the first cycle with lower cattle and input prices offered less opportunity to recover added input cost.

D. Conclusions

This study examined the profitability of three herd size management strategies under a variety of production conditions (fall vs. spring calving and land use intensity) with and without simulated weather effects. Under fall calving, the MA strategy did show higher NPV of cash operating profit and minimum regret when compared to DCA and CHS strategies for the majority of land use intensity \times cattle cycle \times weather effects combinations summarized in Table 2.5. Instituting a MA strategy, however, requires additional time devoted to management in comparison to the CHS strategy and thus producers should weigh this trade-off when considering the use of a MA strategy. For fall calving, looking at the optimal fertilizer use for each cycle (low or medium for the 1st cycle pending weather effects inclusion; medium or high for the 2nd cycle, again, pending weather effects inclusion; and medium for the entire period), regret with

the CHS strategy was less than \$4,250 for any of the periods whether weather effects were included or not. For spring calving operations, this research showed the CHS herd size management strategy to exhibit least regret regardless of land use intensity, weather effects, or cattle cycle. As with fall calving, the highest level of fertilizer use to increase stocking rate, was least profitable and could be discouraged. For both fall and spring calving, LUI regret observations suggested that medium land use intensity, to ensure greater hay sales in comparison to least fertilizer use, was both profit-maximizing in general and led toward the lowest range in cash operating profit. Over the entire period, the above analysis suggested that a producer would have maximized profit, without heightened exposure to income risk, if they had chosen i) fall-calving; ii) not increased stocking rate but added fertilizer to increase hay sales; and, iii) chose the MA herd size management strategy. Noteworthy was that the CHS strategy was a close second choice. This advice held for that period but may well differ for the future.

In contrast to Lawrence (2002), a DCA strategy was not found to be superior to a CHS strategy when examined under a fixed land constraint and resulting on-farm forage limitations. Similar to previous findings (Bentley and Shumway, 1981; Trapp, 1986; Hamilton and Kastens 2000), a counter-cyclical (MA) strategy was found to be more profitable on average than a constant herd size strategy under fall calving conditions with greater cattle output (fewer breeding failures than spring calving). Additionally, previous cow-calf herd management research had not examined a moving average strategy as a method to increase profitability. This research thus contributes to literature on counter-cyclical herd size management strategies by quantifying estimated impacts of capitalizing on cyclical market behavior using a popular investment technique.

While this research examined various management decisions related to fertilizer application, stocking rates, and heifer retention, it was analyzed at relatively small scale and holding land resources constant. At larger scale, marginal gains using the MA strategy are expected to be greater. Further, a 10- to 27-month moving average price ratio was used to signal price trend changes. Different-length moving average prices would lead to different timing of signals and larger increments or decrements in herd size may lead to different outcomes. Finally, FORCAP modeling of weather risk was performed for Northwest Arkansas conditions. These conditions will be different for other regions of the country. Finally, results may differ with year-round calving season management and weather may also impact cattle performance (weight gain and reproductive performance) which was not attempted here.

Footnotes

- ¹ A multitude of other parameters include: grazing method (continuous vs. rotational), use of stockpiling and/or winter annuals, selection of forage species on pasture and hay land, level of fertilizer use, choice of herd genetics, animal weights at different growth stages, supplemental feed, heifer breeding age, breeding failure rates and death losses, calving season, weaning age, year of input and output price, vaccination program, veterinary, and transport charges. While the program tracks ownership charges for equipment, buildings, fence, and watering facilities, these costs are excluded in this analysis as they do not vary significantly when a change in land resources was not considered. Note that changes in breeding stock between 100 and 160 cows were modeled, but effects of minor cow herd changes across time that exist with MA and DCA strategies in comparison to the CHS strategy were excluded. The value of breeding stock was constant over time at long term average prices as effects of timing of industry entry and exit were also not examined.
- ² Fewer than 2% of observations were missing likely due to snow cover as they occurred in December, January, February and April. Missing observations were assigned a value of one, meaning monthly average forage growth was assumed for missing observations.
- ³ Higher and lower interest rates of 10% and 5%, respectively, led to similar results.
- ⁴ It is cost prohibitive for a producer to change calving season from year to year. As such, calving season choice is a long-term decision. Also, fertilizer use decisions, while annually flexible, are complex as weather conditions can affect fertilizer productivity (e.g. applying fertilizer before a drought is ineffective as is a killing frost in late spring or early fall). Hence, the land use intensity choice is considered a long-term decision, especially in the scenario where the breeding herd is expanded.

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F. Tables and Figures

Table 2.1. Sample of Estimated Gross Receipts and Direct Costs of a 100-Cow Herd by Calving Season and Weather Effects in 2004 using Least Fertilizer.

Calving Season Weather Effects	Fall		Spring	
	Excluded	Included	Excluded	Included
GROSS RECEIPTS (% of TOTAL RECEIPTS)				
Steer Calves	\$27,900 (51.2)	\$27,900 (52.2)	\$24,288 (50.7)	\$24,288 (52.7)
Heifer Calves	\$15,079 (27.7)	\$15,079 (28.2)	\$9,913 (20.7)	\$9,913 (21.5)
Cull Cows	\$9,267 (17.0)	\$9,267 (17.3)	\$10,679 (22.3)	\$10,679 (23.2)
Cull Herd Sire	\$1,169 (2.1)	\$1,169 (2.2)	\$1,177 (2.5)	\$1,177 (2.6)
Excess Hay (if any)	\$1,107 (2.0)	\$0 (0.0)	\$1,853 (3.9)	\$0 (0.0)
TOTAL RECEIPTS	\$54,522 (100)	\$53,414 (100)	\$47,909 (100)	\$46,056 (100)
DIRECT COST (% of TOTAL RECEIPTS)				
Fertilizer Costs	\$12,972 (23.8)	\$12,972 (24.3)	\$12,972 (27.1)	\$12,972 (28.2)
Forage Maint. (400 ac) & Winter Annuals (80 ac)	\$9,123 (16.7)	\$9,123 (17.1)	\$9,123 (19.0)	\$9,123 (19.8)
Purchased Hay	\$0 (0.0)	\$5,630 (10.5)	\$0 (0.0)	\$3,864 (8.4)
Salt and Minerals	\$4,420 (8.1)	\$4,420 (8.3)	\$4,340 (9.1)	\$4,340 (9.4)
Veterinary & Drug Charges	\$3,140 (5.8)	\$3,140 (5.9)	\$3,068 (6.4)	\$3,068 (6.7)
Repair and Maintenance	\$2,217 (4.1)	\$2,217 (4.2)	\$2,217 (4.6)	\$2,217 (4.8)
Replacement Herd Sire	\$2,000 (3.7)	\$2,000 (3.7)	\$2,000 (4.2)	\$2,000 (4.3)
Sales commission	\$1,870 (3.4)	\$1,870 (3.5)	\$1,612 (3.4)	\$1,612 (3.5)
Fuel for feeding and checking cattle	\$1,327 (2.4)	\$1,390 (2.6)	\$1,324 (2.8)	\$1,389 (3.0)
Farm Vehicle (\$1 per bred cow per month)	\$1,200 (2.2)	\$1,200 (2.2)	\$1,200 (2.5)	\$1,200 (2.6)
Twine	\$459 (0.8)	\$314 (0.6)	\$463 (1.0)	\$352 (0.8)
Yardage, Ins. & Checkoff	\$248 (0.5)	\$248 (0.5)	\$215 (0.4)	\$215 (0.5)
Custom Hauling	\$225 (0.4)	\$225 (0.4)	\$225 (0.5)	\$225 (0.5)
Corn	\$222 (0.4)	\$336 (0.6)	\$155 (0.3)	\$257 (0.6)
Cattle Purchasing Costs	\$75 (0.1)	\$75 (0.1)	\$75 (0.2)	\$75 (0.2)
TOTAL DIRECT COSTS (TDC)	\$39,497 (72.4)	\$45,159 (84.5)	\$39,989 (81.4)	\$42,909 (93.2)
OPERATING INTEREST	\$938 (1.7)	\$1,073 (2.0)	\$926 (1.9)	\$1,019 (2.2)
CASH OPR. PROFIT (π)	\$14,087 (25.8)	\$7,183 (13.4)	\$7,994 (16.7)	\$2,128 (4.6)

Table 2.2. Sample Monthly Herd Nutrition Needs along with Feeding and Harvesting Statistics as Affected by Weather for a Fall-Calving 100-cow Herd with Least Fertilizer Applied in 2004.

Month	Forage Requirement in cwt ^a to meet Nutrition Needs by Cattle Type						Feeding Statistics in cwt to meet Herd Needs						Est. Days with Feed Supplement		Excess Hay Bales Harvested from Pasture ^f		
	Cows ^b	Bulls	Repl. ^c	Heifer calves ^d	Steer calves ^d	Total	Grazing		Hay Fed		Corn Fed		Excl.	Incl.	Excl.	Incl.	
							Excl. ^e	Incl.	Excl.	Incl.	Excl.	Incl.					
Jan	914	43				957	73	3	884	954	27	40	29	31			
Feb	788	39		24	25	875	356	198	519	677	15	31	17	22			
Mar	828	43		62	61	994	787	740	207	254			6	8			
Apr	767	41		97	103	1008	1008	1008									
May	665	43		143	152	1002	1002	1002								45	
Jun	655	41	77			773	773	773								48	
Jul	689	43	84			815	815	815								44	39
Aug	721	43	89			853	465	360	388	464			14	17			
Sep	692	41	94			827	327	270	500	557			18	20			
Oct	730	43	104			877	683	560	194	318			7	11			
Nov	839	41				880	607	201	273	679			9	23			
Dec	908	43				951	165	115	786	836			26	27			

Notes:

^a Forage requirements are calculated on the basis of drymatter intake needs of the different animal types and their weights given monthly available forage and hay resources. In months where total digestible nutrient intake is insufficient to maintain cow body condition, supplemental corn is fed to cows, replacement heifers and bulls as needed. Crude protein intake is also measured but usually not limiting.

^b Cows are culled as a function of age or if open. All animals culled are sold in May when cows wean their calves that were born the previous October.

- c Replacement heifers are calves fed to replace cull animals and become part of the nutrient needs of the cow herd once 13 months of age.
- d Heifer and steer calves begin grazing at 4 months of age thereby reducing cow nutrition needs.
- e Weather affects forage production and thereby grazing as well as haying activities. The columns titled 'Excl.' show expectations for an average weather year, whereas the column titled 'Incl.' demonstrates the impact of adjusting monthly forage production by the production index as shown in Figure 2.1. Forage quality changes due to weather are not included.
- f In an average weather year, 137 bales, 1,200-lb in weight as is, are harvested from the 320 ac of pasture and 321 bales from 80 acres of hayland. Of the total 458 bales, 409 bales are fed to the herd. In 2004, only 39 and 274 bales are produced on pasture and hayland, respectively, and 517 bales are fed to the herd.

Table 2.3. Sample Monthly Herd Nutrition Needs along with Feeding and Harvesting Statistics as Affected by Weather for a Spring-Calving 100-cow Herd with Least Fertilizer Applied in 2004.

Month	Forage Requirement in cwt ^a to meet Nutrition Needs by Cattle Type						Feeding Statistics in cwt to meet Herd Needs						Est. Days with Feed Supplement		Excess Hay Bales Harvested from Pasture ^f		
	Cows ^b	Bulls	Repl. ^c	Heifer calves ^d	Steer calves ^d	Total	Grazing		Hay Fed		Corn Fed		Excl.	Incl.	Excl.	Incl.	
							Excl. ^e	Incl.	Excl.	Incl.	Excl.	Incl.					
Jan	661	43	98			802	73	2	729	800	18	29	28	31			
Feb	626	39	94			758	356	135	402	623	8	28	15	23			
Mar	687	43	113			842	787	637	56	205			2	8			
Apr	679	41	118			838	838	838									
May	832	43				875	875	875								60	36
Jun	844	41				885	885	885								59	30
Jul	878	43				921	792	867								24	22
Aug	838	43		23	24	927	465	355	463	572			15	19			
Sep	770	41		52	51	914	327	256	587	658			19	22			
Oct	761	43		86	92	982	683	486	299	496			9	16			
Nov	618	41		120	128	906	607	144	300	762			10	25			
Dec	650	43	93			786	165	80	621	705			25	28			

Notes:

^a Forage requirements are calculated on the basis of drymatter intake needs of the different animal types and their weights given monthly available forage and hay resources. In months where total digestible nutrient intake is insufficient to maintain cow body condition, supplemental corn is fed to cows, replacement heifers and bulls as needed. Crude protein intake is also measured but usually not limiting.

^b Cows are culled as a function of age or if open. All animals culled are sold in November when cows wean their calves that were born in April.

- c Replacement heifers are calves fed to replace cull animals and become part of the nutrient needs of the cow herd once 13 months of age.
- d Heifer and steer calves begin grazing at 4 months of age thereby reducing cow nutrition needs.
- e Weather affects forage production and thereby grazing as well as haying activities. The columns titled 'Excl.' show expectations for an average weather year, whereas the column titled 'Incl.' demonstrates the impact of adjusting monthly forage production by the production index as shown in Figure 2.1. Forage quality changes due to weather are not included.
- f In an average weather year, 141 bales, 1,200-lb in weight as is, are harvested from the 320 ac of pasture and 321 bales from 80 acres of hayland. Of the total 462 bales, 380 bales are fed to the herd. In 2004, only 77 and 274 bales are produced on pasture and hayland, respectively, and 491 bales are fed to the herd.

Table 2.4. Summary of Ranch Productivity by Calving Season as Impacted by Fertilizer Application Using a Constant Herd Size Management Strategy Without Weather Effects.

Land Use Intensity	Low	Medium	High
Hayland Fertilizer:			
Ammonium Nitrate in lbs/acre	100	100	300
Poultry Litter in tons/acre	2	2	3
Pasture Fertilizer:			
Ammonium Nitrate in lbs/acre	0	0	100
Poultry Litter in tons/acre	0.5	1	2
# of Cows Bred Annually	100	100	160
Hay Sales - Fall ^a	49	171	46
Hay Sales - Spring ^a	87	221	119

Note:

^a Hay sales are the number of surplus 1,200-lb round bales sold. Hay sales or purchases are a function of seasonal forage production and herd nutrition needs. Weather effects are excluded here but forage production detail is shown in Figure 2.1 as well as Tables 2.1-2.3, 2.5, and 2.6.

Table 2.5. Performance Statistics for Fall Calving Herds by Weather Effects, Cattle Cycle(s), Land Use Intensity and Herd Size Management Strategy.

Period	Land Use Intensity (LUI) ^a		Low			Medium			High		
	Performance Metric	Weather Effects	Herd Size Management (HSM) Strategy ^b								
			CHS	MA	DCA	CHS	MA	DCA	CHS	MA	DCA
1990-2003	NPV of π^c	excl.	45.0	46.3^d	45.0	41.0	43.1	42.7	-1.6	-4.4	-3.5
		incl.	35.9	38.2	38.9	37.6	38.7	37.9	-6.2	-10.6	-9.3
	HSM Regret ^e	excl.	13.0	0.0	12.9	20.9	0.0	4.0	0.0	28.0	19.0
		incl.	31.0	7.9	0.0	10.9	0.0	8.6	0.0	43.6	31.3
	# of Hay Bales Sold ^f	excl.	49(0)	22(20)	3(61)	171(0)	148(18)	129(55)	46(0)	8(25)	-10(98)
		incl.	36(146)	6(140)	-9(131)	168(157)	140(150)	127(146)	56(222)	13(207)	-11(196)
	Head Sold	either	90(0)	93(3)	94(7)	90(0)	93(3)	94(7)	146(0)	148(5)	150(11)
LUI Regret ^g	excl.	0.0	0.0	0.0	39.9	32.1	23.2	466.3	507.3	485.4	
	incl.	17.7	5.6	0.0	0.0	0.0	10.9	438.3	492.9	482.9	
2004-2014	NPV of π	excl.	133.1	136.3	132.2	147.4	151.4	151.2	133.6	136.3	126.2
		incl.	131.2	135.4	131.8	135.3	153.6	137.7	138.9	138.2	128.6
	HSM Regret	excl.	32.3	0.0	40.8	39.9	0.0	2.2	27.2	0.0	100.7
		incl.	42.0	0.0	36.7	182.5	0.0	158.5	0.0	6.8	102.9
	Hay Sold	excl.	49(0)	33(33)	-36(46)	171(0)	157(28)	95(42)	46(0)	44(48)	-76(72)
		incl.	40(102)	26(94)	-42(80)	171(100)	150(92)	89(74)	61(142)	48(136)	-72(113)
	Head Sold	either	90(0)	92(4)	98(6)	90(0)	92(4)	98(6)	146(0)	147(6)	157(8)
LUI Regret	excl.	143.5	151.1	189.7	0.0	0.0	0.0	138.4	151.2	249.8	
	incl.	76.2	181.4	59.6	35.3	0.0	0.0	0.0	153.9	91.6	
1990-2014	NPV of π	excl.	90.3	93.5	90.7	91.2	95.4	94.8	43.8	43.1	40.3
		incl.	76.1	78.9	77.4	83.1	85.9	84.4	32.7	29.0	26.8
	HSM Regret	excl.	32.5	0.0	28.4	42.5	0.0	6.3	0.0	7.7	35.9
		incl.	27.4	0.0	14.6	28.4	0.0	15.5	0.0	37.1	59.0
	Hay Sold	excl.	49(0)	33(33)	-36(46)	171(0)	157(28)	95(42)	46(0)	44(48)	-76(72)
		incl.	38(149)	16(145)	-24(126)	170(156)	148(152)	107(132)	58(216)	28(210)	-38(175)
	Head Sold	either	90(0)	93(4)	96(7)	90(0)	93(4)	96(7)	146(0)	147(6)	157(8)
LUI Regret	excl.	8.9	19.0	41.0	0.0	0.0	0.0	473.5	523.6	545.5	
	incl.	69.6	70.5	69.5	0.0	0.0	0.0	503.3	568.8	575.1	

Notes: Statistical comparisons across annual average outcomes were not performed as a deterministic model was used with the same exogenous price and weather data across herd size strategy \times land use intensity outcomes.

^a Land use intensity is described in Table 2.4. Added ownership charges for larger breeding herds under high land use intensity equated to 31, 27, and 40 thousand dollars of NPV over first, second, and both cycles, respectively.

^b Herd size strategies are: CHS = Constant herd size, MA = counter-cyclical herd size strategy using a moving average price ratio, and DCA = Constant dollar herd reinvestment as described in Eqs. 2.3 – 2.6.

^c Net present value of period-specific, average annual cash operating profits (π) expressed in thousands of dollars or $NPV = \sum_{j=1}^k \frac{\pi_j}{(1+d)^j}$, where j is the year in the cycle, d is the discount rate and k is the number of years in the cycle. Please see Table 1 for cost and revenue items included.

- ^d Bold face indicates optimal herd size management strategy choices on the basis of highest NPV of π for a particular land use intensity level \times period \times weather effects combination.
- ^e HSM Regret for a herd size management choice c for a particular land use intensity level \times period \times weather effects combination is the difference between the highest NPV across herd size management options (as highlighted in bold) and the NPV for the c^{th} herd size management option. Regret is expressed in hundreds of dollars and zero regret identifies the profit-maximizing herd size management strategy for a particular land use intensity level \times period \times weather effects combination.
- ^f The average annual number of 1,200-lb bales. Negative numbers indicate purchases. Numbers in parentheses represent the standard deviation over the period analyzed. Head sold are # of cull cattle and weaned calves.
- ^g LUI Regret identifies the regret (in hundreds of dollars) for a given herd size management strategy across land use intensities for a particular period \times weather effects combination. Zero LUI regret therefore identifies the profit-maximizing land use intensity level by period and weather effects and is again highlighted in bold.

Table 2.6. Performance Statistics for Spring Calving Herds by Weather Effects, Cattle Cycle(s), Land Use Intensity and Herd Size Management Strategy.

Period	Land Use Intensity ^a		Low			Medium			High		
	Performance Metric	Weather Effects	CHS	MA	DCA	Herd Size Management Strategy ^b					
			CHS	MA	DCA	CHS	MA	DCA	CHS	MA	DCA
1990-2003	NPV of π^c	excl.	-7.5	-17.7 ^d	-13.8	-9.0	-18.1	-14.6	-95.5	-104.9	-102.4
		incl.	-13.3	-22.4	-19.5	-14.8	-24.0	-20.3	-104.2	-113.6	-110.8
	HSM Regret ^e	excl.	0.0	102.2	63.2	0.0	90.8	56.2	0.0	93.8	68.9
		incl.	0.0	90.4	61.4	0.0	91.8	54.3	0.0	94.2	66.6
	# of Hay Bales Sold ^f	excl.	87(0)	52(46)	44(68)	221(0)	191(41)	180(66)	119(0)	79(56)	43(107)
		incl.	75(147)	46(142)	34(137)	205(159)	176(158)	166(150)	105(223)	66(220)	28(217)
	Head Sold	either	78(0)	78(4)	80(7)	78(0)	78(4)	80(7)	124(0)	125(6)	128(12)
	LUI Regret	excl.	0.0	0.0	0.0	14.9	3.5	7.9	899.9	891.5	905.6
incl.		0.0	0.0	0.0	15.1	16.5	8.0	908.3	912.0	913.6	
2004-2014	NPV of π	excl.	74.4	71.4	51.7	92.7	90.7	72.7	29.5	28.1	-2.5
		incl.	71.8	70.7	50.9	91.0	89.5	73.4	27.4	27.4	-1.7
	HSM Regret	excl.	0.0	30.7	227.2	0.0	19.7	199.2	0.0	13.6	320.0
		incl.	0.0	10.8	209.0	0.0	15.5	176.6	0.0	0.0	290.9
	Hay Sold	excl.	87(0)	84(35)	-50(78)	221(0)	222(29)	86(78)	119(0)	127(48)	-94(118)
		incl.	76(93)	79(93)	-58(64)	212(101)	213(100)	82(75)	111(140)	124(159)	-98(141)
	Head Sold	either	78(0)	77(3)	86(10)	78(0)	77(3)	86(10)	124(0)	122(5)	137(17)
	LUI Regret	excl.	182.3	193.3	210.3	0.0	0.0	0.0	631.9	625.8	752.8
incl.		192.2	187.5	224.6	0.0	0.0	0.0	636.4	620.8	750.6	
1990-2014	NPV of π	excl.	17.8	6.6	3.0	22.5	12.8	9.4	-85.5	-94.6	-103.0
		incl.	5.6	-3.7	-7.9	10.4	1.1	-1.4	-102.2	-112.4	-118.1
	HSM Regret	excl.	0.0	112.6	147.8	0.0	97.5	131.4	0.0	91.2	175.4
		incl.	0.0	92.7	134.8	0.0	92.5	118.1	0.0	101.7	158.5
	Hay Sold	excl.	87(0)	66(45)	3(86)	221(0)	204(39)	138(85)	119(0)	99(57)	-19(130)
		incl.	78(147)	64(150)	-5(112)	206(156)	192(163)	129(127)	109(211)	88(227)	-27(185)
	Head Sold	either	78(0)	78(4)	82(9)	78(0)	78(4)	82(9)	124(0)	124(5)	132(15)
	LUI Regret	excl.	47.2	62.3	63.6	0.0	0.0	0.0	1080.3	912.4	1030.4
incl.		48.1	48.3	64.9	0.0	0.0	0.0	1126.1	1135.3	1166.5	

Notes: Statistical comparisons across annual average outcomes were not performed as a deterministic model was used with the same exogenous price and weather data across herd size strategy \times land use intensity outcomes.

^a Land use intensity is described in Table 2.4. Added ownership charges for larger breeding herds under high land use intensity equated to 31, 27, and 40 thousand dollars of NPV over first, second, and both cycles, respectively.

^b Herd size strategies are: CHS = Constant herd size, MA = counter-cyclical herd size strategy using a moving average price ratio, and DCA = Constant dollar herd reinvestment as described in Eqs. 2.3 – 2.6.

^c Net present value of period-specific, average annual cash operating profits (π) expressed in thousands of dollars or $NPV = \sum_{j=1}^k \frac{\pi_j}{(1+d)^j}$, where j is the year in the cycle, d is the discount rate and k is the number of years in the cycle. Please see Table 2.1 for cost and revenue items included.

- ^d Bold face indicates optimal herd size management strategy choices on the basis of highest NPV of π for a particular land use intensity level \times period \times weather effects combination.
- ^e HSM Regret for a herd size management choice c for a particular land use intensity level \times period \times weather effects combination is the difference between the highest NPV across herd size management options (as highlighted in bold) and the NPV for the c^{th} herd size management option. Regret is expressed in hundreds of dollars and zero regret identifies the profit-maximizing herd size management strategy for a particular land use intensity level \times period \times weather effects combination.
- ^f The average annual number of 1,200-lb bales. Negative numbers indicate purchases. Numbers in parentheses represent the standard deviation over the period analyzed. Head sold are # of cull cattle and weaned calves.
- ^g LUI Regret identifies the regret (in hundreds of dollars) for a given herd size management strategy across land use intensities for a particular period \times weather effects combination. Zero LUI regret therefore identifies the profit-maximizing land use intensity level by period and weather effects and is again highlighted in bold.

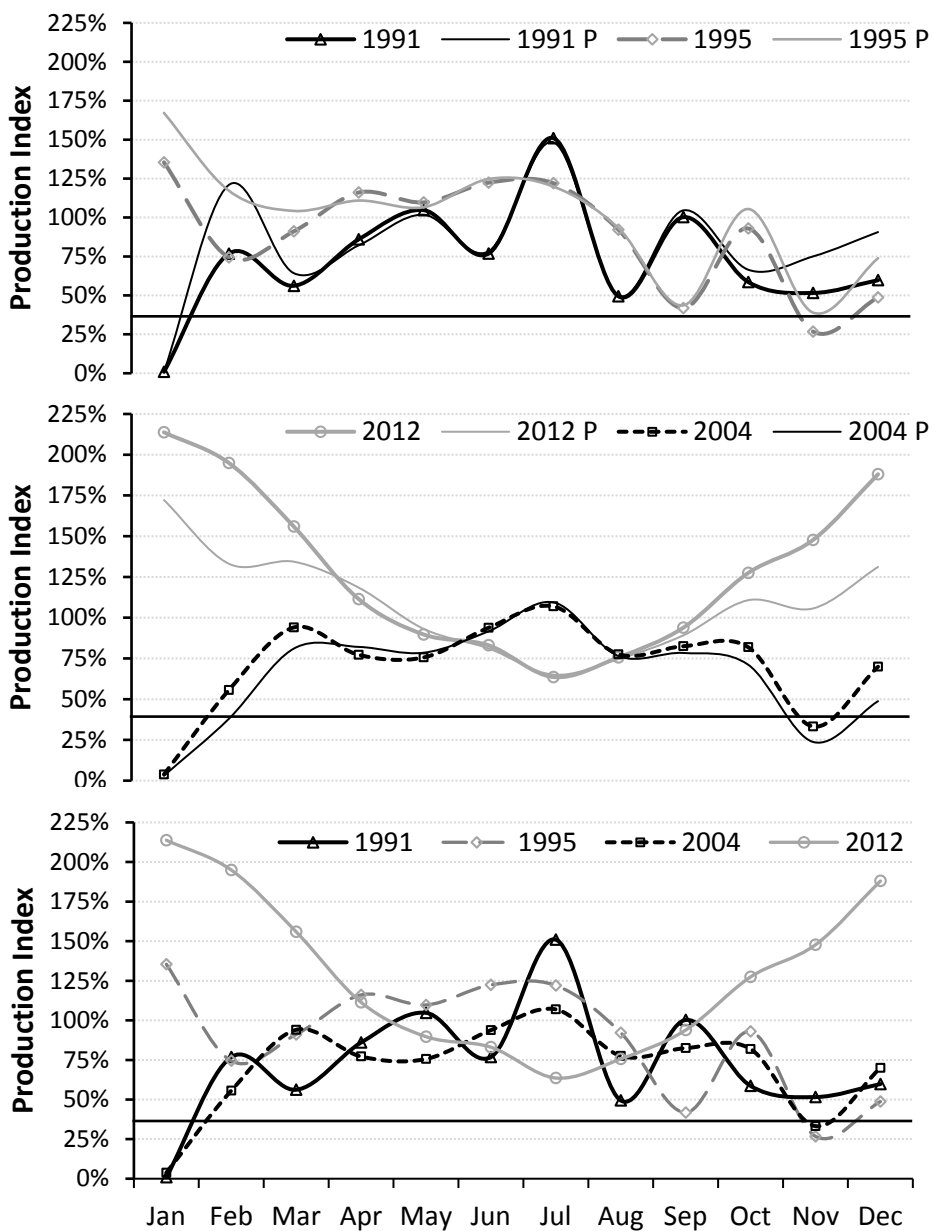


Figure 2.1. Forage production index values by month and year for select years using 25-year and period specific (P) averages in the denominator for the production index.

Notes: Percentage values represent standardized production index values as specified in Eqs. 2.1 and 2.2 for select years shown. A production index value of 100% represents an expected production year. Using period specific production indexes (top two panels), as opposed to the long run production index (bottom panel), impacts forage production adjustments mainly for winter months. Noticeably, and not isolated to the select years shown, forage production is slightly higher using the period specific index compared to the long run index in the first cycle and the obverse is true for the second cycle.

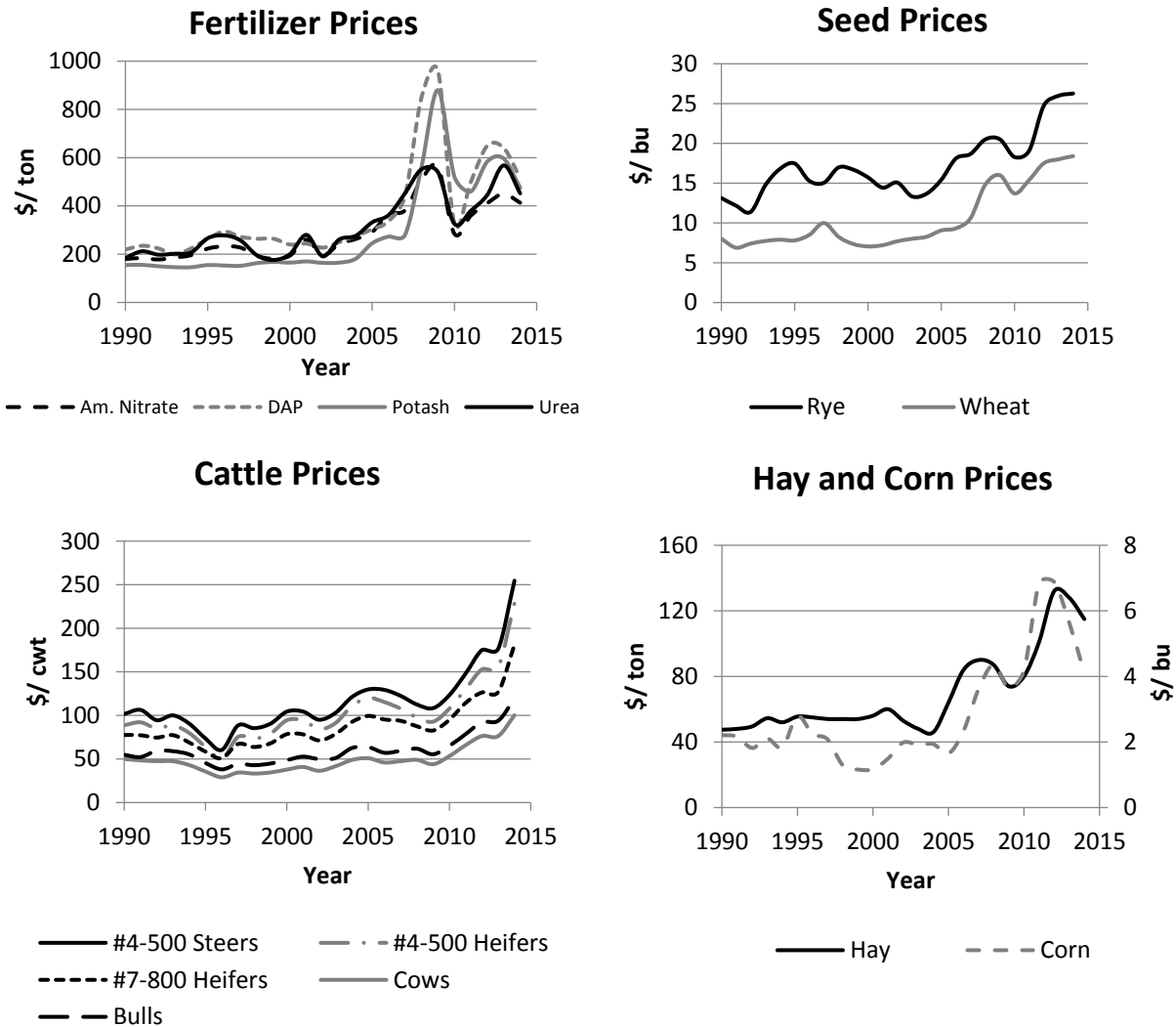


Figure 2.2. Nominal prices for major input and output prices, 1990-2014.

Notes: Only one weight category of calf prices is exhibited due to calf prices by weight category moving in a similar direction over time. 7-800lb heifer prices are shown as a reference for heifer replacement costs. Cattle prices shown are annual averages but are higher for fall calving operations than spring calving operations once adjusted for monthly seasonal differences.

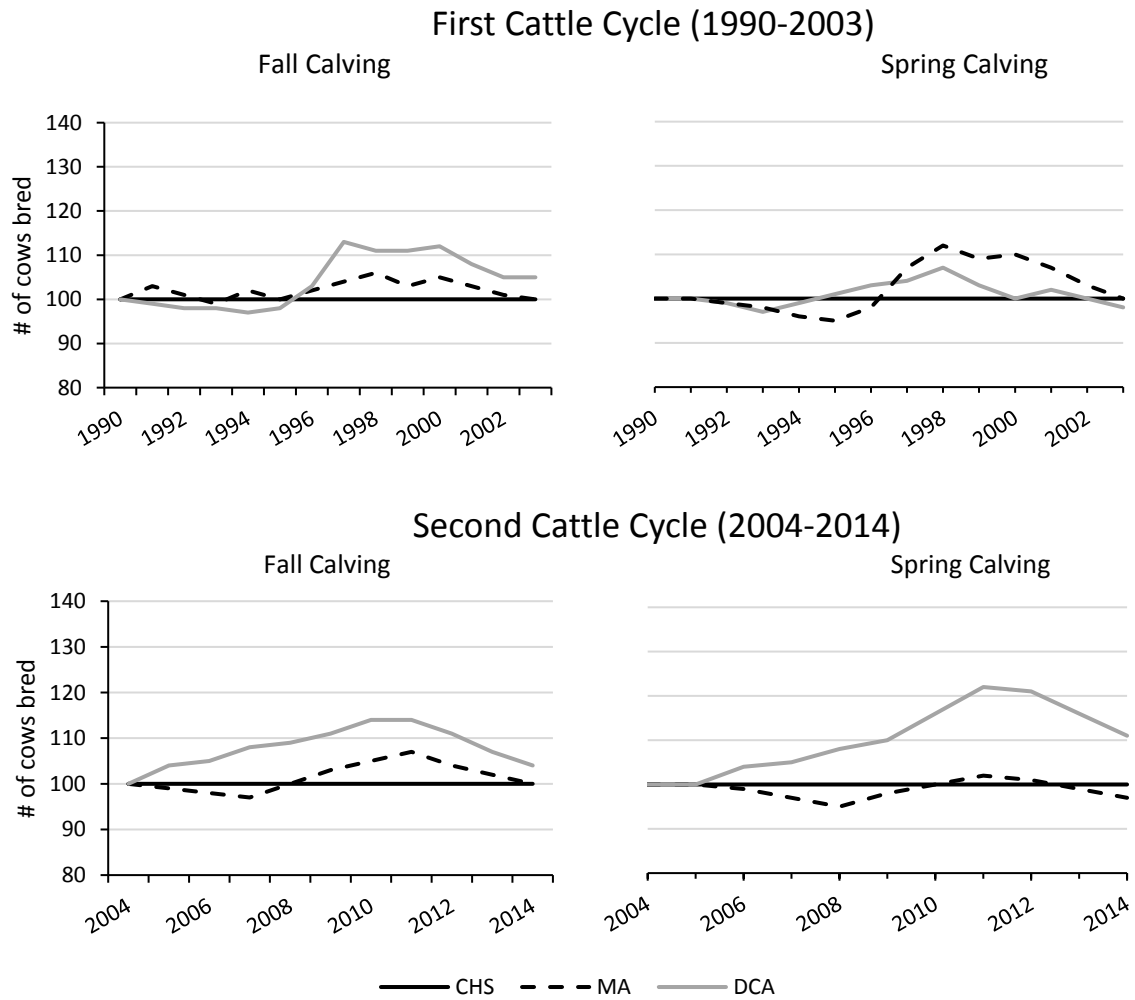


Figure 2.3. Breeding Herd Sizes by Strategy and Period Analyzed for Fall and Spring Calving Herds.

Note: The constant herd size (CHS) strategy leads to no change in cow herd size. The moving average (MA) strategy uses a ratio of two moving averages of feeder steer prices to signal an up- or downtrend in cattle prices with herd expansion/liquidation on downtrend/uptrend signal. The dollar cost averaging (DCA) strategy as described in Eqs. 2.3 – 2.6 keeps replacement heifer investment constant over time. 160-cow herd sizes are not shown as same trends are evident.

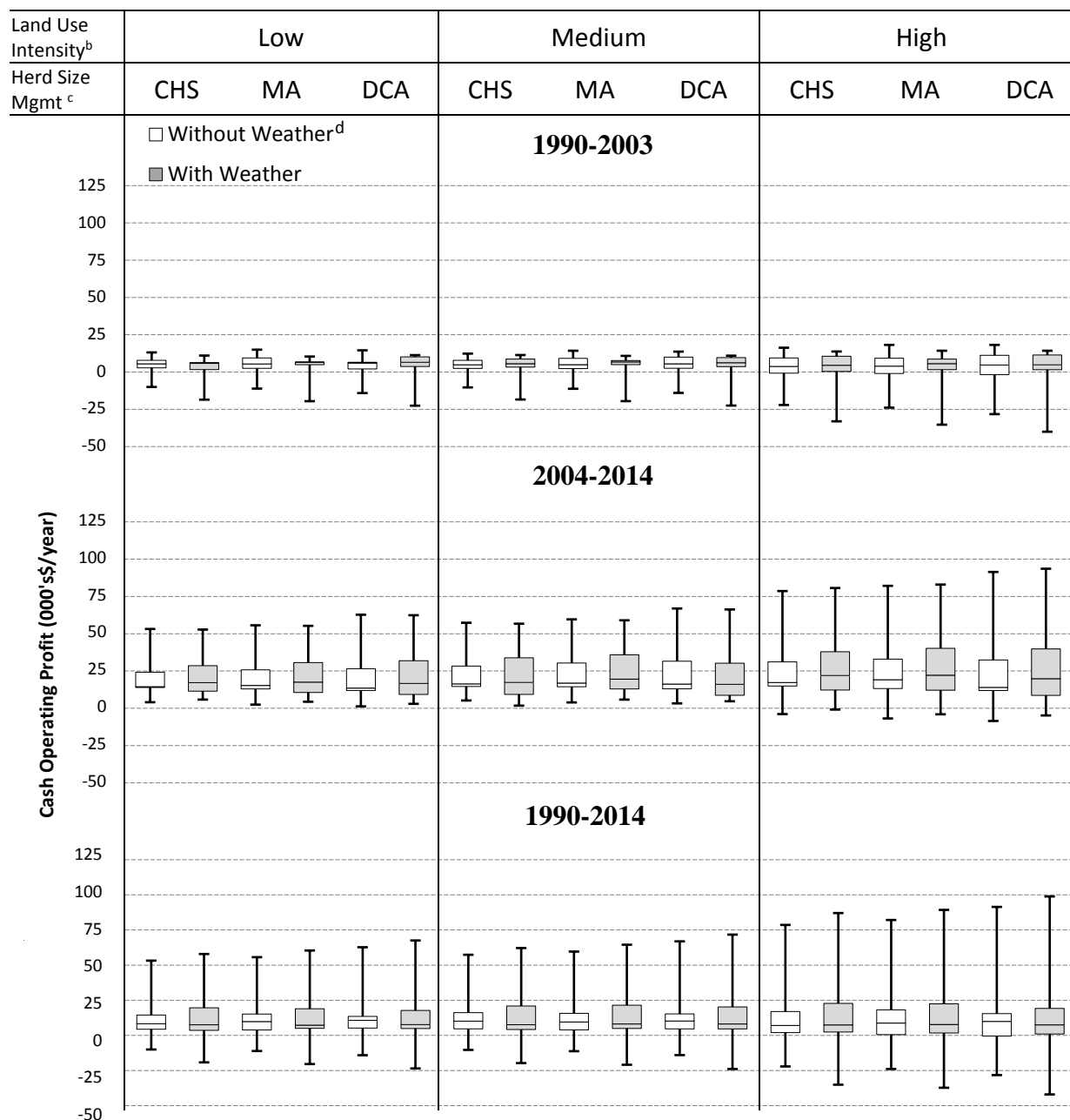


Figure 2.4. Minimum, Median, Maximum, and 25th and 75th Percentiles of Cash Operating Profit^a for Fall Calving Herds by Land Use Intensity, Herd Size Management Strategy, and Cattle Cycle or Time Period With Weather Effects Excluded and Included.

Notes:

^a Cash operating profits are averages, period-specific, and are calculated as the sale of cattle and hay less costs for supplements, seed, fuel, fertilizer, twine, chemicals, vet services, op. interest, repairs and medicine in \$/year.

^b Land use intensity is described in Table 2.1.

- c Herd size strategies are: CHS = Constant herd size cow herd size, MA = cow herd size strategy using a ratio of two moving averages of feeder steer prices to signal an up- or downtrend in cattle prices, and DCA = dollar cost averaging strategy as described in Eqs. 2.3 – 2.6.
- d See Figure 2.1 for production index adjustment due to weather conditions.

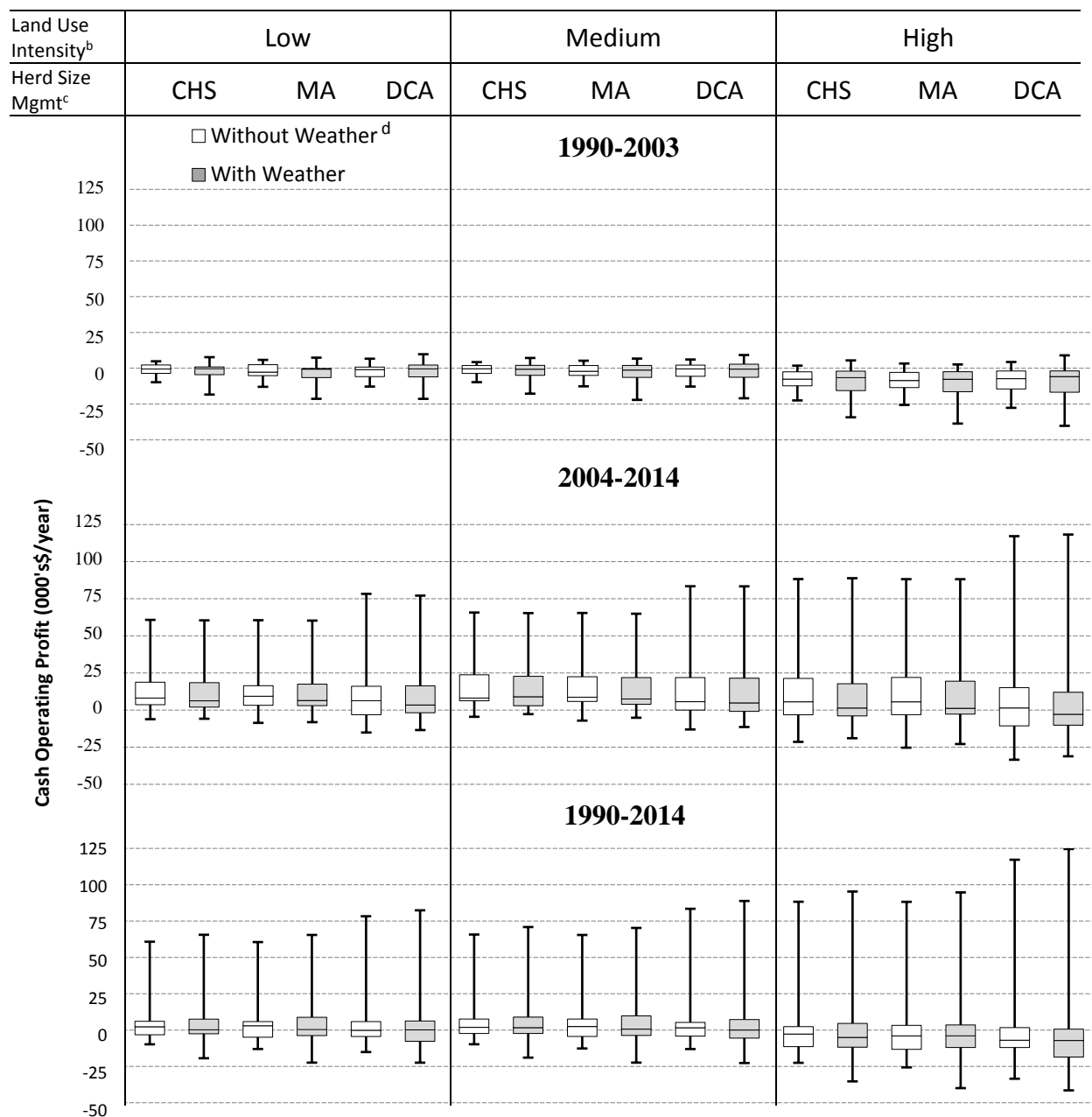


Figure 2.5. Minimum, Median, Maximum, and 25th and 75th Percentiles of Cash Operating Profit^a for Spring Calving Herds by Land Use Intensity, Herd Size Management Strategy, and Cattle Cycle or Time Period With Weather Effects Excluded and Included.

Notes:

^a Cash operating profits are averages, period-specific, and are calculated as the sale of cattle and hay less costs for supplements, seed, fuel, fertilizer, twine, chemicals, vet services, op. interest, repairs and medicine in \$/year.

^b Land use intensity is described in Table 2.1.

- ^c Herd size strategies are: CHS = Constant herd size cow herd size, MA = cow herd size strategy using a ratio of two moving averages of feeder steer prices to signal an up- or downtrend in cattle prices, and DCA = dollar cost averaging strategy as described in Eqs. 2.3 – 2.6.
- ^d See Figure 2.1 for production index adjustment due to weather conditions.

Chapter III. Profitability Impact Analysis of Price Variables and Herd Management Decisions in Cow-calf Operations

A. Introduction

Tester et al. (2019) provided a 25-year analysis of three herd size management (HSM) strategies in terms of relative profitability and risk across the two most recent cattle cycles with and without simulated weather effects on forage production. Their analysis revealed that when employing a fall calving season, a price signal-based, counter-cyclical herd size management strategy involving a ratio of two different-length moving average prices, was able to generate larger net present value of cash operating profits than a constant herd size strategy. Under spring calving conditions, on the other hand, a constant herd size management strategy was profit-maximizing. Across calving seasons, fall calving was shown to be the profit-maximizing decision due to decreased breeding failure rates when compared to spring calving. Additionally, Tester et al. (2019) suggested a medium level of fertilizer use (Table 2.4) to be profit-maximizing as that level of input use i) led to more hay sales than a lesser fertilizer use strategy with the same number of cattle; or ii) was less expensive than a strategy with more fertilizer and added cattle output. They also noted that the medium fertilizer use level was less risky than using more fertilizer and similar in risk compared to lesser fertilizer use because added hay sales led to less reliance on cattle sales. For both analyses, land resources and equipment were held constant. As a result, weather impacts on forage production either created conditions of excess hay sales or required purchase of hay to meet herd nutrition requirements. With many variables impacting profitability of cow-calf operations over time, quantifying the relative impact of key variables on profitability was left unanswered. Since different econometric and neural network techniques exist and can rank the relative impact of choice of HSM strategy, level of fertilizer use, stocking

rate, and calving season on cow-calf profitability, this paper examines two different modeling techniques.

The objective of this research is to examine the relative impact of explanatory variables on cow-calf operations' profitability across the previous two cattle cycles when production is managed using different HSM strategies, calving seasons, fertilizer input and stocking rate. Two modeling techniques, ANN and regression, are used to determine whether these techniques lead to the same ranking of explanatory variables based on their relative impact as calculated using Eq. 3.1 and how the modeling techniques compare in terms of goodness-of-fit (R^2). The point of the comparison is to determine if using the more interpretable and computationally easier regression approach comes at the cost of sacrificing considerable explanatory power. As such, quantifying the magnitude and consistency of this tradeoff is needed.

Traditionally, regression analysis has been the foundational statistical technique for data analysis in economics. Regression analysis allows examination of the effects of one or more explanatory variables on a dependent variable where variables can be continuous, discrete, or categorical (Weisberg, 2013). These techniques allow assessment of statistical significance of relationships observed and then quantifies those relationships using parameter estimates that can ultimately be used to make predictions.

With the growth of big data and advanced artificial learning, artificial neural network (ANN) analyses are becoming more popular as a viable alternative to traditional regression analysis. Despite demonstrated superior goodness-of-fit in many applications, ANNs are not easily interpretable and provide less insight when compared to regression analysis. Parameter estimates of explanatory variable effects on the dependent variable are not revealed in a structured, user-defined manner but instead estimated as a neural network of cause and effect

relationship that are iteratively determined by weighting a myriad of functional forms (Olden and Jackson, 2002) and/or a variety of ANN configurations. Multi-Layer Feedforward Networks (MLF) and Generalized Regression Neural Nets (GRNN) are described here as they are relevant ANN configurations using Neural Tools v 7.5® (NT) software (Palisade, 2015). MLF networks function through a backpropagation algorithm and include one or more hidden layers that specify the relationships between explanatory variables (Figures 1.1 and 1.2). These relationships are weighted to minimize the sum of squared errors using a training process, involving large numbers of iterations that require significant processing time. The inclusion of more than one hidden layer increases complexity and often increases processing time. To make predictions, the user requires NT software as parameter estimates are hidden.

Generalized regression neural net configurations are distinctly different from MLFs. Rather than manipulating relationships between explanatory variables and their connection to the dependent variable, GRNNs adjust the smoothness parameter to minimize the sum of squared errors (Figures 1.4 and 1.5) The smoothness parameter determines the influence of observations on the predicted value as a function of their proximity to the desired output value obtained from the training set (University of Wisconsin, n.d.). Again, NT software is required for predictions.

Further, NT and similar software exist to assist with the choice of i) ANN framework to use (GRNN vs MLFs with varying levels of nodes in a single hidden layer); and, ii) the percentage of the original data set to use for training of the neural net vs. the percentage used for testing predictions of the neural net. The user specifies the number of iterations used to minimize error in the training runs and the program picks random observations for training the neural net (Palisade, 2015). As such, ANN outcomes vary with the percentage of the data set used for training, the type of ANN (GRNN vs. MLF), and because the training data are chosen randomly

although at the same percentage. Once a neural net is trained, however, ‘live’ predictions are based on the estimated neural network for a given training percentage and given set of random training values. However, a different training on the data set, leads to different predictions, even with the same percent of observations used for training. Much like regression analysis ANNs use R^2 to measure explanatory power. Further, NT, an Excel Addin, reports relative impacts of explanatory variables on the dependent variable as follows:

$$(3.1) \quad I_i = \Delta_i / \sum_{i=1}^n \Delta_i$$

where Δ_i is the difference between predicted maximum and minimum outcomes when changing the explanatory variable i across observations in the training data set holding all other explanatory variables constant and n is the number of explanatory variables. The i^{th} impact on the dependent variable is then compared to the sum of all n explanatory variables’ impacts, calculated the same way, to yield relative impacts for each explanatory variable that sum to 100% across all explanatory variables. This same formula can be used with outcomes from regression analysis as described below.

It should be noted that an exact measure of variation explained could be determined in alternative fashion. The cow/calf simulation tool, the Forage and Cattle Planner (FORCAP), that generated the data analyzed within (Tester et al. (2019); Popp et al., 2014), uses a large set of parameters in input values to estimate profit over time, i.e. the costs of all relevant inputs, all relevant output prices and the implicit technology (production function) that, in this case, also includes the role of weather. Dixon et al. (1987) demonstrate that conventionally estimated profit functions do not always results in good replications of underlying technology so that it is useful and informative to investigate alternative approaches. The underlying technologies in

Dixon et al. (1987) are smoothly continuous but those in FORCAP, are not, further motivating the need to explore alternative methods for ranking variable importance.

In the applications that follows, ANNs and regression methods are used in a curve-fitting exercise. As noted earlier, conventional economic theory leads to profits and optimal derived demand levels that are determined from conventional profit functions. The models estimated below include output prices for both outputs (cattle and hay) as well as their prices. In the case of hay, its price serves as both an output price and an input price. Fertilizer price and other input prices are not included since they play a minor role (Table 2.1). By including output of hay and cattle as well as fertilizer input use, both exogenous and endogenous variables in relation to profit are being included. Hence it is not possible to impute any causal or behavioral relationships but simply measure via regression or ANN how profit varies as the explanatory variables (production, cattle prices and input use) change. In essence regression and ANNs are being used to estimate the shape of a more complex function and derive information about that more complex function. The analysis is thus intended to showcase what variables drive most of the variability in profit and thereby which variables are most important for a producer to monitor.

B. Materials and Methods

1. Data

Profitability estimates of 1,800 annual cow/calf operation simulations as described in Tester et al. (2019) were used to measure the relative impact of a variety of explanatory variables such that:

$$(3.2) \quad Y_j = \alpha_0 + \alpha_1 HayQ_j + \alpha_2 HayP_j + \alpha_3 CattQ_j + \alpha_4 CattP_j + \alpha_5 FertM_j \\ + \alpha_6 FertH_j + \alpha_7 Weather_j + \alpha_8 Season_j + \varepsilon_j$$

where Y_j is cash operating profits in year j defined as the revenue generated from cattle and excess hay sales less production costs, $HayQ_j$ is the annual number of 1200-lb bales sold/bought, $HayP_j$ is the annual price of hay in dollars per ton, $CattQ_j$ is the yearly number of calves, cull cows, and cull bulls sold, $CattP_j$ is the nominal 4-500 lb steer price that varied by calving season, $FertM_j$ and $FertH_j$ were binary (zero/one) variables denoting intermediate and highest fertilizer use (Table 2.4) in comparison to the least fertilizer use of the baseline, respectively, $Weather_j$ is a weather index indicating above/below cattle cycle or period-specific annual forage production that averages to 1 for a particular cattle cycle or period, $Season_j$ represents whether or not the operation utilizes a spring or fall calving season in a particular year, and ε_j is the error term. Equation 3.2 was then estimated for each of the three time periods, the 1990-2003 cattle cycle, the 2004-2014 cattle cycle, and finally over both time periods.

2. *Explanatory Variable Selection*

Since the variables initially identified to model operating profitability were likely to be correlated leading to multicollinearity (causing point estimates to be imprecise), principal component analysis was used to determine the appropriate number of explanatory variables to use. Four principal components were able to explain roughly 98% of the variation in the explanatory variables (Figure 3.1). This suggests the potential to eliminate several explanatory variables i) by using their statistical significance/contribution to model performance such that explanatory variables with $|t\text{-stat}| < 1$ were dropped (the adjusted R^2 criterion); and, ii) by examining the extent of correlation among explanatory variables to avoid redundancy due to strong multicollinearity. The results suggested that hay price was statistically insignificant in every period analyzed, and hay sold was highly correlated with weather as expected since the weather index drove forage production. Hay sold remained in the model given it's ease of

interpretation relative to the weather index and its larger |t-stat|. Finally, calving season was removed because the primary effect of a spring calving season is higher expected breeding failures that result in fewer head sold. Therefore, head sold captured the majority of calving season effects while cattle price captured seasonal price effects resulting from selling calves in the fall rather than the spring.

Additionally, ANN analysis was conducted using the initial set of explanatory variables. Similar to the regression results, the ANN model's variable impact analysis revealed calving season, weather, and hay price to have little impact. Fertilizer was also shown to have little impact in the ANN, but provided substantial explanatory power in the regression and therefore was included. Using these results, the final model specification included cattle price, hay sold, head sold, and fertilizer application level as follows:

$$(3.3) \quad Y_j = \beta_0 + \beta_1 HayQ_j + \beta_2 CattQ_j + \beta_3 CattP_j + \beta_4 FertM_j + \beta_5 FertH_j + \gamma_j$$

where γ_j was the error term and other variables were as described for Eq. 3.2. Selection of explanatory variables was held constant across cycle or time period as well as modeling technique.

3. *Artificial Neural Network Analysis*

Neural network analysis was conducted using NT (Palisade, 2015). The "Best Net Search" tool was used to select the configuration that resulted in the lowest root mean square error for data sets that were separated by time period with the following results -- GRNN for the 1990-2003 cycle; MLF with 5 nodes for the 2004-2014 cycle; MLF with 6 nodes for the 1990-2014 period.

To test for the consistency of ANN modeling outcomes across cattle cycle and for the entire period, ANN analyses were repeated 10 times using randomly selected observations from

training data sets that differed in size -- two training runs each with 80%, 75%, 70%, 65%, and 60% of the data. This led to ten observations of variable impacts and ten estimates of R^2 to determine if the ranking of relative variable impacts would change across model runs and also by cattle cycle or time period analyzed.

4. Regression Analysis

To allow comparison of R^2 and variable impact analyses between regression models and ANNs, randomly selected training data used in the ANN analyses were also used as the data set for regression analysis. For example, 403 random observations of the 504 observations in the 1990-2003 cycle were used in each of the two 80/20 training/testing runs of the ANN. For each corresponding regression model, these same 403 observations were used. Statistical significance of input variables was computed using heteroskedastic consistent standard errors using the *coefstest* function of the *lmtest* package for R (Zeileis and Horton, 2002). Finally, while R^2 was automatically reported for regression output, R^2 of ANN models were calculated using:

$$(3.3) \quad R^2 = 1 - \frac{\sum(\hat{Y}_i - Y_i)^2}{\sum(\bar{Y} - Y_i)^2}$$

where \bar{Y} is the mean annual cash operating profitability (Y_i) in the randomly selected training data set for which a prediction \hat{Y}_i was made.

Further, regression coefficients for each explanatory variable were used to determine their impact on profitability for direct comparison to ANN analysis results. As such,

$$(3.4) \quad I_{HayQ} = \frac{\beta_1 \cdot [HayQ_{max} - HayQ_{min}]}{\sum_{i=1}^n \Delta_i}$$

was the relative impact of variable $HayQ$ on Y or I_{HayQ} , Δ_{HayQ} was calculated as shown in the numerator and represented the maximum change in \hat{Y} with changes in $HayQ$ using coefficient estimates of Eq. 3.3 and holding other variables constant, and i represented the i^{th} of n

explanatory variable impacts. Note that for the fertilizer effect, a binary zero/one variable, the maximum change \hat{Y} is reflected in the coefficient estimate of the highest fertilizer use dummy variable and as such the fertilizer impact was calculated as follows:

$$(3.5) \quad I_{Fert} = \frac{\beta_5}{\sum_{i=1}^n \Delta_i}$$

C. Results

ANN models outperformed regression in every instance by the R^2 criterion. This was not surprising as neural networks examine a host of linear and non-linear combinations of explanatory variables' impacts on the outcome whereas a linear functional form was used in the regression models (Eq. 3.3). Across all three cycles or periods, ANN models had average R^2 values between 96.9% and 98.5%. In comparison, regression models generated average R^2 values of 90.4% to 92.1% using identical, randomly selected training data sets (Table 3.1).

For the 1990-2003 cycle, the ANN models identified cattle price as the most impactful variable by a significant margin, 14.7%, over the second most impactful variable, number of hay bales sold. Cattle price had an average impact of 43.2% compared to 28.5% for hay sold and was followed by head sold and fertilizer, respectively (Figure 3.2).

In the regression analysis, all variables were significant at the $p=0.001$ level for all ten model specifications. In terms of variable impacts, head sold was the most impactful variable and was followed by hay sold, fertilizer, and cattle price. Hay sold showed a slightly higher average impact over cattle price and fertilizer, but also had a much larger range of impact estimates. Fertilizer and cattle price impacts were separated by 0.3% across the 1990-2003 cycle (Figure 3.2).

For all four variables, ANN models had a larger range of variable impacts compared to the regression models. This suggested that ANN modeling of dependencies between explanatory

variables and the predicted outcome varied more by randomly selected data sets used in comparison to changes in effects observed when a simple linear fit was imposed as with the regression model.

For the 2004-2014 cycle, cattle price remained the most impactful variable in every ANN model and garnered a larger average impact with smaller range of impacts when compared to the 1990-2003 cycle. In opposition to the previous cycle, head sold was more important than hay sold while fertilizer remained the least impactful variable (Figure 3.2). In the regression analyses, all variables were statistically significant at $p=0.001$ with the exception of the effect of medium fertilizer application, which was significant at $p=0.01$ or $p=0.05$ depending upon the model run. When examining regression results, variable impact rankings were similar but not identical to ANN rankings. ANNs showed hay sold to be slightly more impactful than fertilizer, while regression revealed the opposite (Figure 3.2).

For the 25 year period, 1990-2014, cattle price was consistent as the most impactful variable under all ANN model runs. The margin between cattle price and the second most impactful variable, head sold, was the largest, 20.5% on average, across the 25-year period when compared to the individual cycles. The two least impactful variables, hay sold and fertilizer, were consistent with the second cycle (Figure 3.2). In accordance with the previous cycle, all five coefficients were highly statistically significant ($p<0.001$) and variable impact rankings were identical to the previous cycle. Average variable impacts were separated by less than 2% across techniques and hence rankings between ANNs and regression were the most similar of any of the periods analyzed.

D. Conclusions

1. Variable Impacts

Artificial neural network analysis revealed cattle price to be the most impactful variable in every model and analysis period, but this result was only the same for regression analysis in the 2004-2014 cycle and the 25-year period. Head sold was the second most impactful variable in ANN analysis for the 2004-2014 cycle and 25-year period, whereas head sold ranked third for the 1990-2003 cycle. This result was accompanied with a large range of variable impact observations, 17.2%, for hay sold over the first cycle. Hence hay sold was not always the second most impactful variable. Variable impacts calculated using linear regression coefficients resulted in similar results as those observed with ANN results as cattle price was the most impactful variable over the 2004-2014 cycle and the 25-year period. During the first cycle, observed cattle prices varied less in comparison to other periods (Figure 2.2), and hence head sold was shown to have a larger impact over the first cycle. Fertilizer application level was consistently the least impactful variable for ANNs and third most impactful for regression analysis. Artificial neural networks generated larger range of impacts in every model period when compared to regression analysis. This highlights the criticism of ANNs as random selection of observations and size of training set led to a large range of results even when using a consistent network configuration (BestNet Search was not employed for each model run).

2. Producer Management Decisions

Results were consistent across both modeling techniques in that cattle price and head sold were the most impactful revenue variables impacting cash operating profits. Cattle producers are price takers and therefore cattle price cannot be influenced by producer's management decisions outside of modifying calving season to potentially capture a seasonal price advantage in the

spring months when selling calves born in fall and forage production is plentiful. Fall calving herds are thus able to capture an advantage over spring calving operations by selling at seasonally higher prices and modeling supported this conclusion. With respect to head sold, a positive regression coefficient (β_2) suggested that increasing the number of head of cattle sold increased profits. This suggested that lower breeding failure rates or larger herd size would be profit-maximizing (Table 3.1). However, more cattle will consume more forage and hence greater cattle output leads to lower hay sales or requires more fertilizer. One method to increase head sold without creating large increases in forage requirements is to use fall calving with fewer breeding failures than spring calving. Results from this analysis therefore reinforce Tester et al.'s (2019) conclusion that fall calving was the profit-maximizing choice for producers regardless of cattle cycle.

Adding more fertilizer, to increase forage production and thereby cattle or hay sales, on the other hand showed pronounced negative effects (β_4 and β_5) in Table 3.1 which could be offset by greater cattle and/or hay sales (β_1 , β_2 , and β_3). However, those impacts are not easily discernable from the variable impacts reported by ANNs (Fig. 3.2). Regression coefficients lend themselves more to examining this tradeoff than ANN results, although NT users can use 'live' predictions. Neither ANNs or regression analysis portray clearly that fertilizer at the medium level was profit-maximizing as shown in Chapter II. Using live predictions in NT would allow a user with the software to develop predictions for certain management practices that may eventually lead them to that profit-maximizing choice.

Tester et al. (2019) also pointed out that dollar cost averaging and countercyclical herd size contraction and expansion decisions based on price signals led to more head sold than a management practice of maintaining the herd at a constant size over time. Results from ANN

and regression analysis indicate that head sold is an important factor in terms of profitability. From a perspective of herd size management strategy, a dollar cost average strategy which led to the largest amount of cattle sales could thus erroneously be interpreted as the profit-maximizing decision when using ANN or regression results. Reduced excess hay sales with more cattle, offset such a recommendation which is not easily shown using the variable impact results.

3. *Modelling Technique Limitations*

In terms of model performance, ANNs were shown to be a superior predictive technique in terms of R^2 . This result is similar to the findings of Lek et al. (1996) in an alternate application regarding brown trout nesting rate. This superior goodness-of-fit did not come without cost, however, as hidden layers are not revealed given the complexity of describing the relationships of a trained neural network. As such, model results for making predictions are useful only to those with access to software like NT. Retraining the network also leads to changing results. Without an explicit description of relationships between explanatory variables and the dependent variable, as is available with regression analysis in the form of size and sign of parameter estimates (Table 3.2), it is therefore difficult to interpret results of a trained neural network in the absence of having access to 'live' predictions in NT. Employing the live prediction capability of ANNs does allow examination of marginal changes in projected profitability. Specifying a set of inputs and varying for example, fertilizer application rate or number of head sold is a viable alternative to analyzing regression coefficients. This approach would allow for a variety of scenarios to be examined quickly, but also would require access to large amounts of data as well as software such as NT. This investment may be deemed appropriate by large producers whose management decisions have large financial implications, but for many producers, knowledge of regression coefficients, may present sufficient information for making more informed decisions.

4. *Study Limitations and Future Research*

Future research is needed to determine if the results and conclusions of this paper are consistent across further time periods and geographic regions. This analysis was Northwest Arkansas-specific and encompassed only the previous two cattle cycles. As such results may be different for future cattle cycles. Additionally, as the use of ANNs becomes more prevalent, software may allow for more detailed analysis of the trained network results. Development of more transparent software would lend itself to more regression analysis comparisons in the future.

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F. Tables and Figures

Table 3.1. Estimation of the Effects of Hay Production, Cattle Sales, and Fertilizer Use on Annual Estimates of Cow-calf Cash Operating Profits using Linear Regression and Comparing Goodness-of-Fit with Artificial Neural Network Techniques of Generalized Regression Neural Networks (GRNN) for 1990-2003, Multilayer Feed Forward Neural Networks (MLF) with 5 nodes for 2004-2014 and 6 Nodes for 1990-2014 Across 10 Model Runs per Time Period.

Time Period:	Variable		Regression Coefficients		
			Minimum ^a	Average	Maximum
1990-2003	HayQ ^b	β_1^c	27	29 ^{***,d}	30
	CattQ	β_2	370	388 ^{***}	398
	CattP	β_3	419	432 ^{***}	447
	FertM	β_4	-4,086	-3,818 ^{***}	-3,432
	FertH	β_5	-25,081	-24,742 ^{***}	-24,087
	R²		0.899	0.904	0.910
			GRNN		
R²		0.979	0.985	0.993	
<hr/>					
Time Period:	Variable		Regression Coefficients		
			Minimum ^a	Average	Maximum
2004-2014	HayQ ^b	β_1^c	42	44 ^{***}	49
	CattQ	β_2	657	706 ^{***}	730
	CattP	β_3	432	449 ^{***}	462
	FertM	β_4	-3,822	-3,041 ^{*/**}	-2,614
	FertH	β_5	-36,234	-34,469 ^{***}	-31,836
	R²		0.916	0.921	0.928
			MLF 5 Nodes		
R²		0.981	0.985	0.987	
<hr/>					
Time Period:	Variable		Regression Coefficients		
			Minimum ^a	Average	Maximum
1990-2014	HayQ ^b	β_1^c	30	32 ^{***}	35
	CattQ	β_2	516	549 ^{***}	562
	CattP	β_3	388	407 ^{***}	421
	FertM	β_4	-3,723	-3,054 ^{***}	-2,579
	FertH	β_5	-30,720	-29,921 ^{***}	-28,630
	R²		0.915	0.920	0.927
			MLF 6 Nodes		
R²		0.965	0.969	0.972	

Notes:

- ^a Modeling was performed 10 separate times for each time period using different randomly selected subsamples of the data with different proportions used for training the neural net (60%-80%). Randomly chosen observations were the same for regression vs. ANN analyses for each model run.

- ^b *HayQ* was the annual number of 1200-lb bales sold/bought, *CattQ* was the yearly number of calves, cull cows, and cull bulls sold, *CattP* was the nominal, Arkansas average 4-500-lb price for medium and large frame No. 1 steers that varied by calving season and served as a proxy for all types of cattle sold, *FertM* and *FertH* were binary zero/one variables denoting intermediate and highest fertilizer use in comparison to the least fertilizer use of the baseline, respectively.
- ^c See Eq. 3.3.
- ^d * = $p < 0.05$ level, ** = $p < 0.01$ level, and *** = $p < 0.001$ level.

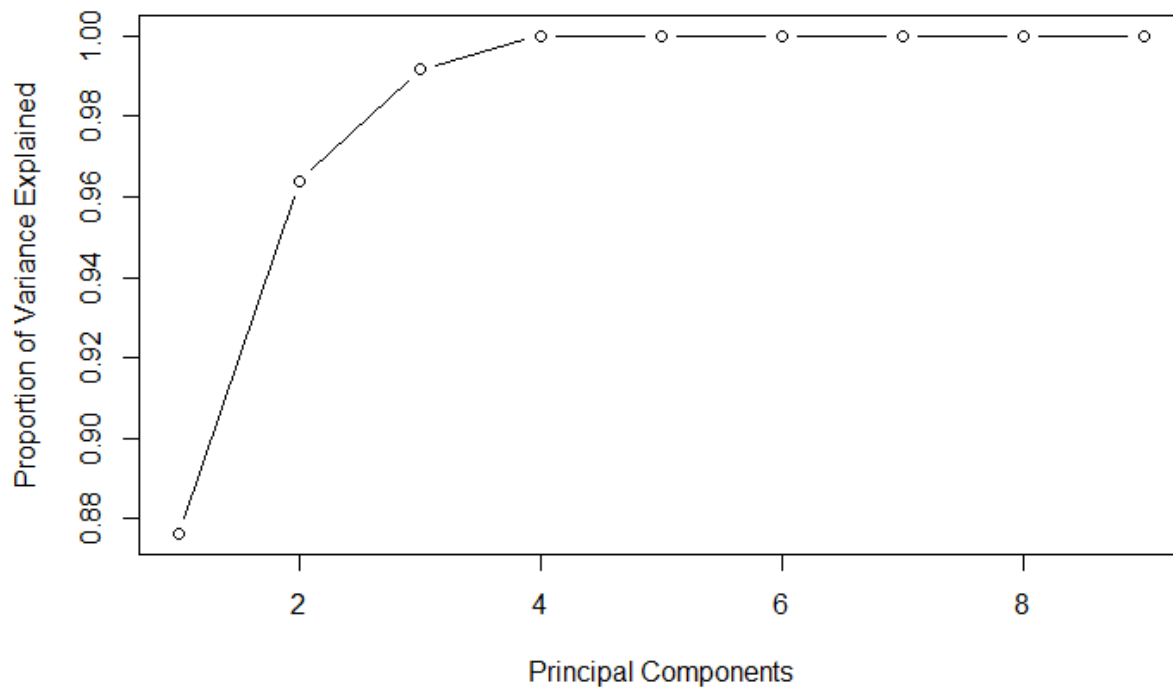


Figure 3.1. Principal Component Analysis for Variable Selection to Explain Cow-calf Cash Operating Profits using Hay and Cattle Sales, Fertilizer Use, Calving Season and Weather over 1990-2014.

Note: The dependent variable was Y_j or cash operating profits in year j defined as the revenue generated from cattle and excess hay sales, $HayQ_j$ was the annual number of 1200-lb bales sold/bought, $HayP_j$ was the annual price of hay in dollars per ton, $CattQ_j$ was the yearly number of calves, cull cows, and cull bulls sold, $CattP_j$ was the nominal 4-500 lb steer price that varied by calving season, $FertM_j$ and $FertH_j$ were binary zero/one variables denoting intermediate and highest fertilizer use in comparison to the least fertilizer use of the baseline, respectively, $Weather_j$ is a weather index indicating above/below cattle cycle or period-specific annual forage production that averages to 1 for a particular cattle cycle or period, $Season_j$ represents whether or not the operation used a spring or fall calving season in a particular year.

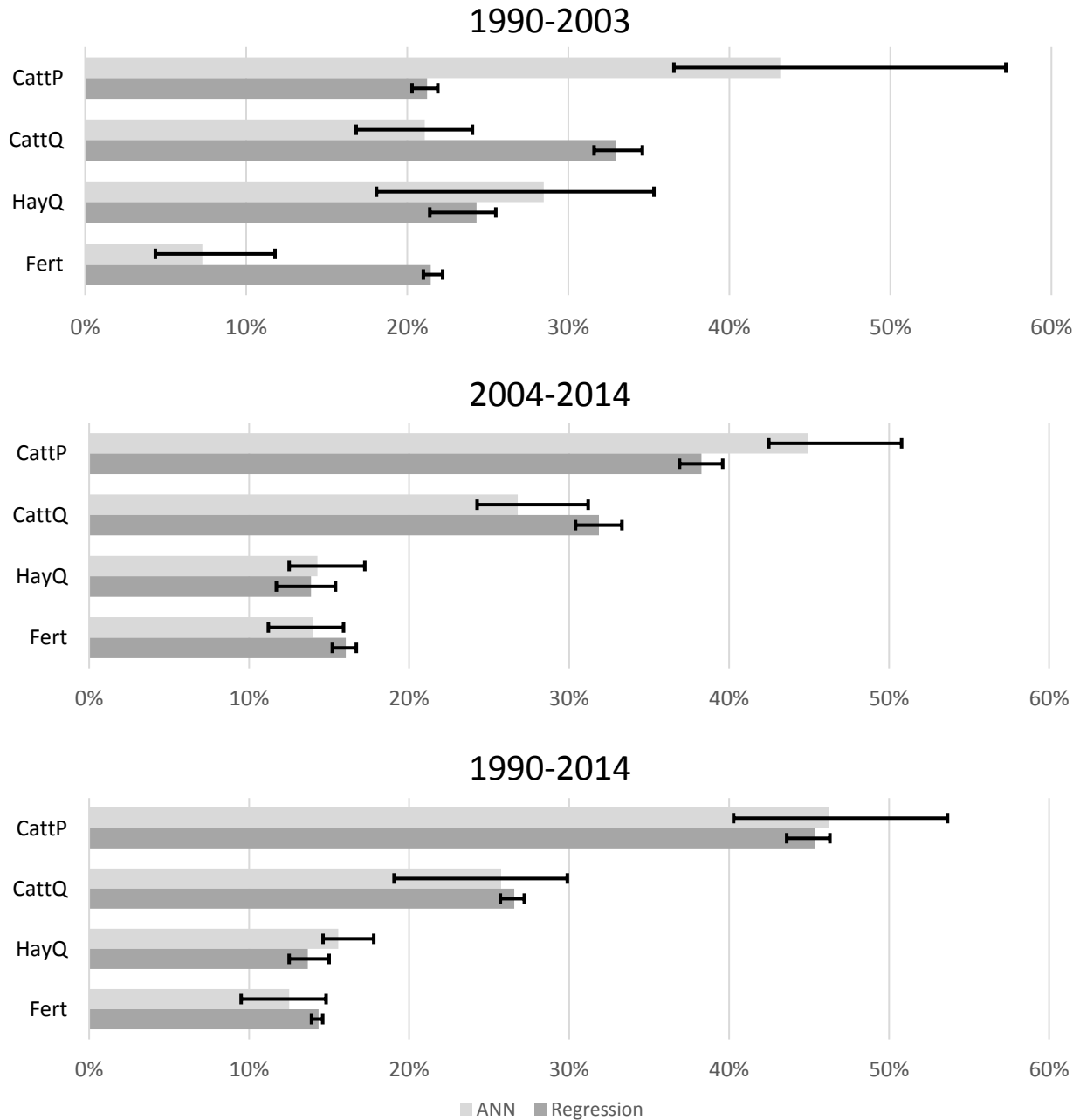


Figure 3.2. Comparison of Variable Impact Analyses: Minimum, Average, and Maximum Variable Impacts as Estimated Repeated across Cycle or Period Using Different Randomly Selected Training Sets of Varying Size.

Note: *HayQ* was the annual number of 1200-lb bales sold/bought, *CattQ* was the yearly number of calves, cull cows, and cull bulls sold, *CattP* was the nominal, Arkansas average 4-500-lb price for medium and large frame No. 1 steers that varied by calving season and served as a proxy for all types of cattle sold, *FertM* and *FertH* were binary zero/one variables denoting intermediate and highest fertilizer and their effect was combined using Eq. 3.5.

Chapter IV. Summary of Conclusions and Considerations for Future Research

A. Summary of Results and Conclusions

In Tester et al. (2019), three herd size management strategies were evaluated on the basis of cash operating profit across two cattle cycles, 1990-2003 and 2004-2014 as well as two calving seasons. This analysis examined a variety of production scenarios utilizing a fixed land base both with and without weather effects on forage production. The null hypothesis was that price-signal based herd management strategies would not increase profitability or decrease income risk when compared to a constant herd size strategy. Results from this analysis demonstrated that a countercyclical herd expansion/contraction strategy involving a price signal, based on the ratio of two different length moving average steer prices, did lead to slightly higher profit using fall calving regardless of weather effects on forage production. That strategy also did not deleteriously affect income risk. However, a constant herd size strategy was shown to be the profit-maximizing and income risk neutral strategy when calves are born in the spring. The above strategies exhibited highest returns using a medium level of fertilizer with added hay sales in lieu of greater stocking rates for both fall and spring calving herds. In the opinion of the author, marginally larger profits generated by the countercyclical strategy were not large enough to recommend this strategy to producers. Larger operations, with larger herds may turn to this strategy as greater profitability ramifications to changing herds size management strategy are expected.

Chapter III employed two modeling techniques to describe the relative impact of hay and cattle sales, calving season, weather, and fertilizer use on cow-calf operating profits using performance observations as estimated in Tester et al. (2019). Artificial neural networks were compared and contrasted with regression analysis on the basis of goodness-of-fit (R^2) and

ranking of relative impacts of explanatory variables. The null hypothesis was that relative impact rankings would be the same across techniques. A second null hypothesis was that model predictive performance was the same across techniques. Results from this analysis demonstrated that ANNs possessed greater R^2 for modeling cow-calf profitability than regression analysis. However, regression analysis results were more interpretable and easily accessible to users. In all three time periods, ANN analysis revealed cattle price to be the most important driver of profitability. Variable impact results using either modeling technique led to similar rankings in most cases. Coefficient signs and magnitudes from the regression analysis reinforced the conclusions presented in Tester et al. (2019). However, both linear regression coefficients and ANN do not easily point to profitability implications when tradeoffs among variables need interpretation. Medium fertilizer use showed a negative coefficient, for example, but was the profit-maximizing choice. For ANNs, variable impacts do not describe whether changes in a variable lead to a positive or negative impact but rather only indicate relative impact in comparison to other variables. A user of ANNs needs to employ live prediction capabilities of ANNs to analyze marginal changes in profitability as a result of changing production decisions such as fertilizer application rate or stocking rate. As highlighted in the analysis, these marginal changes are sensitive to training and testing data sets and therefore are unlikely to yield consistent conclusions. Live prediction analysis would require significant investment in software and data collection and, in the opinion of the author, would only be justifiable for large-scale operations.

B. Study Limitations and Future Research

This research examined three herd size management strategies under a fixed land resource over a 25-year period. The marginal gains in profitability generated using a

countercyclical rather than constant herd size strategy may be large enough to constitute implementation at a larger scale. Additionally, results presented in this research were specific to the previous two cattle cycles and may not hold in future cycles. Simulated weather conditions were also specific to northwest Arkansas and will differ based upon the region of analysis. Results presented in chapter III were generated using a specific functional form or network configuration as well as a limited set of explanatory variables. Results and conclusions are subject to change with changes in modeling technique or selection of explanatory variables.

Future research may examine these research questions under a larger land constraint as well as different regions using different forages and price series. Additionally, non-linear functional forms of regression analysis as well as differing network architectures for ANNs could be explored. As ANN analysis techniques continue to improve, greater transparency of relationships may be possible.

C. References

Tester, C., Popp, M., Nalley, L. and N. Kemper. 2019. "Impact of Weather and Herd Size Management on Beef Cow Profitability." *Journal of Agricultural and Applied Economics*. In Press.