TEMPERATURE DRIVEN DIET QUALITY PREDICTION FOR FREE-RANGING CATTLE

A Dissertation

by

YINGJIE ZHANG

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2008

Major Subject: Rangeland Ecology & Management

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Approved by:

Chair of Committee,	Urs Kreuter
Committee Members,	J. Richard Conner
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ABSTRACT

Temperature Driven Diet Quality Prediction for Free-ranging Cattle. (August 2008)

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A rapid and accurate method to determine or predict cattle diet quality is essential to effectively manage free-ranging cattle production. One popular tool currently available for predicting cattle diet quality is fecal Near Infrared Reflectance Spectroscopy (NIRS) profiling, which requires considerable time and financial investment. Two approaches were taken to develop a replacement of NIRS fecal analysis for predicting real-time cattle diet quality. The first approach took advantage of a standing forage quantity monitoring and prediction model, and its animal diet selection sub model to model cattle diet quality. The second approach tested if a direct relationship is present between cattle diet quality and a simple temperature driven variable.

The model used in the first approach is Phytomass Growth Model (PHYGROW). Using the Growing Degree Days (GDD) concept, forage crude protein estimation equations were developed. Coupled with PHYGROW diet selection sub model, cattle diet quality values were modeled. The validation study revealed good correlation between predicted diet quality and observed diet quality (r^2=0.84).

The Grazing Animal Nutrition lab (GAN lab) commercial fecal NIRS analyzing data for Major Land Resource Area 42 (MLRA 42) was used to analyze the relationship between GDD and cattle diet crude protein (CP). Repeatable high quality regressions were found for CP and GDD. A simple temperature based model was then developed to predict cattle diet quality for regional use. Another independent dataset for MLRA 116B from the GAN lab fecal NIRS data and a controlled grazing study were used to validate the relationship. The study showed that using GDD to predict cattle diet quality is a dependable tool, but regional specific relationships need to be developed.

The two developed models set the foundation for remotely predicting cattle diet quality for effectively managing cattle production. The approaches also set the framework for developing broader applications for other animal species.

DEDICATION

To Dr. Jerry Stuth, for the great research opportunity he offered me and the valuable insight he left to the world.

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I would like to thank Dr. Urs Kreuter for serving as my committee chair. Special thanks to Dr. Jerry Stuth for also serving as my committee chair before his tragic death. I also want to thank Dr. Douglas Loh, who previously served as my major professor, together with Dr. Richard Conner and Dr. Jason Sawyer for serving on my Ph.D. advisory committee and for their assistance, insights and direction.

Thanks to Dr. Doug Tolleson, Jay Angerer, Kris Banik, Stephen King and Tim Brown for their support and guidance with the grazing trial and the PHYGROW and NUTBAL models. Thank you, also, to Jimmy Wu and Will Shaw for your technical support. I also want to thank the whole GAN Lab staff and all the student workers for helping me handle the sampling, the experimental animals and the fecal samples.

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CHAPTER I

INTRODUCTION

Founded in 1991 under Texas A&M University System agricultural program, the Center for Natural Resource Information Technology (CNRIT) developed a series of information management and decision support tools for planning, monitoring and assessing natural resource management systems. The Phytomass Growth Model (PHYGROW) and The Nutritional Balance Analyzer (NUTBAL) are two of the most adopted tools for forage and livestock management purposes.

The Ranching Systems Group (RSG) within the Center CNRIT has been working for over 15 years to develop a new suite of technologies that help mitigate the risk of drought and improve the adoption of released technologies. In 1997, the United States Agency for International Development (USAID) Global Livestock Collaborative Research Support Program (GLCRSP) funded a project to develop a Livestock Early Warning System (LEWS) for East Africa. The approach adopted has subsequently been configured for use in Texas as part of a LEWS pilot program. It also served as the basis for design of a new National Range and Forage Loss Insurance program administered by USDA-Risk Management Agency. PHYGROW is the foundation technology used in LEWS for monitoring the impact of emerging weather events on livestock forage supply both in Texas and in the pastoral regions of East Africa.

This dissertation follows the style of *Rangeland Ecology and Management.*

PHYGROW is a hydrologic-based plant growth simulation model that predicts standing crop under certain management criteria. It represents the complex interaction between numerous soil characteristics, plant community characteristics, grazing practices and weather data for a particular location (Stuth et al. 2003a). The animal diet selection sub model within PHYGROW enables it to simulate the kind and amount of forage being selectively consumed by certain animals and thereby calculates the available forage for a particular kind of animal. The diet selection sub model places plant species into five preference categories (Preferred, Desirable, Undesirable, Toxic and Emergency) and computes the proportion of each preference class in the diet. The animal preference of a plant species can be assigned by a user according to phenological stage: fast growth, declining growth, quiescence, dormancy and dead (Quirk and Stuth 1995). PHYGROW has been widely used in Texas, Oklahoma, New Mexico, East Africa and Mongolia.

The NUTBAL model predicts nutrient intake, requirements and balance of protein and energy for grazing animals based on the physiological characteristics of the animals, the prevailing forage quality and availability, and weather conditions. It also estimates body weight change, identifies the primary limiting nutrient (energy or protein) and calculates dry matter intake via fecal output. Lyons and Stuth (1992) first showed that Near Infrared Reflectance Spectroscopy (NIRS) technology could be used to identify key organic chemical bonds in animal feces and successfully predict dietary constituents which formed the precursors to the formation of those bonds in the feces. This concept resulted in the development of NIRS equations for scanning feces and predicting the diet crude protein (CP) and digestible organic matter (DOM) of free-ranging animals (Lyons and Stuth 1992; Coates 1998; Gibbs et al. 2000; Gallagher 1990; Keating 2005). The Ranching Systems Group at Texas A&M University group subsequently provided a diet evaluation service based on NIRS fecal analysis to the public. Dr. Jerry Stuth, Grazing Animal Nutrition Lab (GAN Lab) Director, then further incorporated the technology into a nutritional balance profile (NUTBAL) software program. Since 1994, NUTBAL has helped producers, managers, and consultants to make more informed feeding and grazing management decisions. These methods are in use throughout the U.S. and the world to detect forage nutrient deficiencies and identify the most cost efficient supplemental strategies to meet production goals.

One of the most important categories of inputs in NUTBAL relates to diet quality and includes CP, DOM, and the DOM/CP ratio of the diet being consumed by the animals under consideration. The DOM/CP ratio is an indicator of ruminal efficiency (McCollum 2004), which is an important factor for animal performance output in NUTBAL. Ruminal microbes need a balanced supply of energy and protein. Typically, a DOM/CP ratio of 4 results in peak fermentation rates in the rumen and optimum performance. DOM/CP ratios greater than 7-8 indicates amount of energy available to microbes exceeds the amount of available protein and limits microbial activity. When DOM/CP ratios are below 4, intake is suppressed with reductions up to 65% when the ratio approaches 2.5 due to the negative effects of excess ammonia formation in the rumen (Stuth 2001). Currently, input data for CP and DOM for NUTBAL are derived from fecal samples analysis. GAN lab provides a service to analyze fecal samples in which NIRS technology is used to predict dietary CP and DOM on a dry matter basis, and fecal phosphorus and nitrogen. Currently, the nutritional profiles based on results provided by GAN Lab are in use throughout the U.S. and in other countries across the globe for domesticated livestock such as cattle, goats, and sheep and for wildlife such as bison, elk, and deer.

Although NIRS fecal analysis is a relatively precise and rapid method for estimating dietary CP and DOM, it has some disadvantages. The average price is $25 per sample, which represents a considerable investment for users wishing to consistently analyze samples at the landscape scale. Furthermore, this approach requires users to collect fecal samples and deliver them to the GAN Lab in Texas. Depending on the sampling location, the delivery time varies from 2 to 7 work days. After the samples are received, they need to be dried and prepared for analysis, which usually requires 2 additional days. Therefore, the NUTBAL results could take 5 to 10 days to reach the users accounting for all these processes. The cost, the labor needed and the time lag are major deficiency of NUTBAL as a predicting tool for time sensitive decision making purposes.

This research here is dedicated to overcoming this deficiency by developing alternative approaches for predicting animal diet quality for NUTBAL or for other management applications instead of using NIRS fecal analysis data. The model will serve the dual purposes of (1) adding a diet quality prediction function to PHYGROW and (2) providing an alternative approach of predicting animal diet quality for NUTBAL instead of using fecal analysis data. Success of the model will link two powerful tools (PHYGROW and NUTBAL) together to predict forage quantity and quality consumed by concerned animals and thus remotely monitor and predict animal performance. Two approaches are used to address these objectives. One is using standard weather data to predict forage quality and integrate with PHYGROW's animal diet selection model to produce animal diet quality model. The other approach is to find a direct way to predict animal diet quality without using the diet selection sub model in PHYGROW through analyzing of GAN lab's commercial fecal NIRS diet quality data.

Since animal nutrient intake and, therefore, animal performance, are the product of the quantity and the nutritional quality of the consumed forage, both need to be predicted. The PHYGROW animal diet selection sub-model converts the predicted standing crop to animal intake by plant species. Thus, PHYGROW predicts the quantity of the animal intake by species. A predictive method that can estimate forage quality by species would serve as the link between PHYGROW and NUTBAL.

The animal diet quality model developed will be a new component of PHYGROW. It will update PHYGROW's performance to not only predict forage quantity but also forage quality and diet quality of grazing animals. The output of this addition to the PHYGROW model could be directly used as an input in NUTBAL to predict animal performance instead of fecal derived NIRS values. The integrated model is best suited for landscape scale analysis when cost of fecal analysis is expensive. A successful forage quality prediction model itself would be of great benefit for managers to support decisions about timing of harvest which optimizes the combination of forage quality and quantity.

The dissertation is organized in 6 parts: (1) Introduction, in this part the need of developing an animal diet quality model and the background information is introduced. (2) Background and State of Knowledge, forage quality and diet quality concepts and importance in literature are discussed in this part, followed by specific reviews of Growing Degree Days as an effective predictor for forage quality, animal diet selection sub model in PHYGROW and the GAN lab dataset for the second approach of my objectives. (3) Development of a Cattle Diet Quality Model Using Temperature Data and PHYGROW, using GDD as a predictor for forage quality, coupled by the animal diet selection sub model in PHYGROW, an animal diet quality model is developed in this part and validated by a grazing trial study. (4) A Simple Temperature Driven Animal Diet Quality Model, this part address the second approach in my objectives. By analyzing the GAN lab commercial data, a simplified model is developed to predict animal diet quality solely based on temperature data. (5) Summary and Conclusion, two approaches to meet the objectives are valuated and the applications of the models developed are discussed. (6) Literature Cited.

CHAPTER II

BACKGROUND AND STATE OF KNOWLEDGE

The first approach of the research involves development of a forage quality model, integrated with the diet selection sub model in PHYGROW to predict animal diet quality. Review of the literature here includes aspects of forage quality and animal diet selection sub model in PHYGROW. The second approach of the research involves analyzing the GAN lab commercial data to develop a simplified animal diet quality prediction model, so a review of the GAN lab dataset is also included for the purpose.

Forage quality

Forage quality is crucial for the livestock industry. They provide essential energy, proteins, vitamins, minerals and fibers for livestock production. Forage quality is defined as the sum total of the plant constituents that influence an animal's use of the feed and ultimately its performance (Ball et al. 2001). This is influenced by environmental factors including radiation, temperature, day length, plant-available soil water and plant-available nitrogen and phosphorous. Forage quality also varies with plant species and season and location of growth (Ball et al. 2001). Range forage is often optimal for livestock growth and production for only a short period of the year. Early in the growing season, forage has a high nutrient concentration, but indicators of high forage quality such as protein, energy, vitamins, and minerals decline proportionally as the growing season progresses, while indicators of low quality, such as fiber and lignin, increase as forage plants mature (Adesogon et al. 1993). Plant maturity has been viewed as the primary factor affecting forage quality (Kalu and Fick 1981; Perry and Baltensperger 1979), George and Bell (2001) regressed CP on stage of maturity and explained the variation for six annual grasses (r^2=0.79), filaree (r^2=0.76), and bur clover (r^2=0.71).

Evaluating and predicting forage quality is complex. Historically, forage quality has been assessed on physical factors like maturity, softness, color and leafiness (Ball et al., 2001). Although this simple method is important, they are very subjective and difficult to standardize.

Wet chemistry analysis is the conventional method to more accurately determine the components of forage. It is based on well-established chemical principle to determine the quantity and type of chemical compounds in a forage sample. Although it's an accurate method, the slow turnaround time and expense associated with it restrained its use.

Near Infrared Reflectance Spectroscopy (NIRS) is a computerized method of forage testing. It has been successfully used to predict forage quality for livestock through clipped forage (Barton and Burdick 1983; Park et al.1983; Marten et al. 1984). NIRS method greatly reduces the sample turnaround time.

Either physical, wet chemical or NIRS method are only capable of assessing forage quality at a point of time or after samples being collected. The need to predict forage quality for making timely management decisions in line with future situation is not addressed.

Total nitrogen (N) or crude protein (usrally N × 6.25) is one of the most commonly used indicators for forage quality. Researchers have compared different empirical approaches including growing degree days (GDD), day of the year (DOY), mean stage count (MSC), and mean stage weight (MSW) to predict forage CP (Mitchell et al. 2001; Moore et al. 1991; Kalu and Fick 1981; Hill et al. 1995).

Mitchell et al. (2001) found that GDD (r^2=0.91) was the best method for predicting CP values compared to DOY (r^2=0.82), MSC (r^2=0.87) and MSW (r^2=0.84) for Switchgrass (*Panicum virgatum)*, and also the best method for predicting CP values for Big blustem (*Andropogon gerardii)* with r^2=0.90 compared to DOY (r^2=0.81), MSC (r^2=0.62) and MSW(r^2=0.67). Similarily, Borreani et al. (2003a) also found GDD (r^2=0.62) is a better predictor for forage quality than MSW (r^2=0.47) and DOY (r^2=0.31) for nutritive value of sulla (*Hedysarum coronarium*) at two Mediterranean sites (Ancona and Sassari, Italy). Hill et al. (1995) found that GDD (r^2=0.83) was a better predictor for CP levels in AU-Triumph tall fescue (*Festuca arundinacea)* than MSC (r^2=0.35) & MSW (r^2=0.61). West et al. (1991) also proposed GDD (r^2=0.98) as a better predictor than DOY (r^2=0.87) for CP in winter wheat.

Among these predictor variables, only GDD incorporates ambient air temperature in its definition (Undersander 1997). GDD calculates the heat accumulation above a minimum threshold temperature for plant growth, often referred to as the base temperature (Undersander 1997). The accumulation equation commonly used is:

$$GDD= (T_{max}+T_{min})/2-T_{base} \qquad [1]$$

where T_{max} is the daily maximum temperature, T_{min} is the daily minimum temperature and T_{base} is a species specific base temperature required for growth.

Temperature is the driving force behind most physiological processes that occur in a plant, including translocation of nutrients and cell wall formation, both of which directly influence forage quality (Undersander 1997). It is reasonable then that GDD will produce good predictions of forage quality. To compare equations relating GDD to CP from various sources, they were rearranged to correspond to the following standardized format:

$$CP = a\ (GDD-b)^2 + c \qquad [2]$$

where a, b and c are constants and their meaning will be discussed later.

The equation developed by Mitchell et al. (2001) to predict CP for Switchgrass (10ºC base temperature, Equation 3) with r^2 0.95 and RMSE 9:

$$CP\ (g/kg) = 263.85 - 0.30\ (GDD) + 0.0001\ (GDD)^2 \qquad [3]$$

Equation 3 can be reformatted as Equation 3'.

$$CP\ (g/kg) = 0.00010\ (GDD-1500)^2 + 38.85 \qquad [3']$$

The same authors developed an equation to predict CP for Big bluestem from GDD (10ºC base temperature, Equation 4) with r^2 0.96 and RMSE 9:

$$CP\ (g/kg) = 277.32 - 0.31\ (GDD) + 0.0001\ (GDD)^2 \qquad [4]$$

The equation can be reformatted as Equation 4':

$$CP\ (g/kg) = 0.00010\ (GDD-1550)^2 + 37.07 \qquad [4']$$

Smart et al. (2001) also developed 2 equations to predict CP for Big bluestem based on GDD during each of 2 trials (5 ºC base temperature) for non-grazed pasture. The trial 1 equation (Equation 5) had r^2 0.79 and RMSE 16.15:

$$CP\ (g/kg) = 223 - 0.197\ (GDD) + 0.0000612\ (GDD)^2 \qquad [5]$$

It can be reformatted as Equation 5':

$$CP\ (g/kg) = 0.00006\ (GDD - 1610)^2 + 64.47 \qquad [5']$$

The second equation Smart et al. (2001) developed to predict CP for Big bluestem (5 ºC base temperature) for non-grazed pasture (trial 2, Equation 6) had a r^2 0.94 and RMSE 10.70:

$$CP\ (g/kg) = 220 - 0.256\ (GDD) + 0.0000932\ (GDD)^2 \qquad [6]$$

It can be reformatted as Equation 6':

$$CP\ (g/kg) = 0.00009\ (GDD - 1373)^2 + 44.21 \qquad [6']$$

Hill et al. (1995) developed an equation to predict Tall fescue CP (a cool season grass; 5 º C base temperatures) in which NRATE is an independent variable for the N fertilizer applied in kg /ha. This equation (Equation 7) had a r^2 0.82 and RMSE 19:

$$CP\ (g/kg) = 263 - 0.3499\ (GDD) + 0.000156\ (GDD)^2 + .2384*NRATE \qquad [7]$$

Since the variable 0.2384NRATE does not affect the constants ‘a’ &’b’ in the standardized equation (Equation 2). Equation 7 can be reformatted as Equation 7' in which d is a constant related to available N fertilizer.

$$CP\ (g/kg) = 0.00016\ (GDD-1122)^{2} + d \qquad [7']$$

Borreani et al. (2003a) developed an equation (Equation 8) using GDD to predict CP in Sulla (a legume, 5 ºC base temperature) with r^2 0.62 and RMSE 25:

$$CP = 0.000078\ GDD^2 - 0.227\ GDD + 288 \qquad [8]$$

It can be reformatted as Equation 8':

$$CP\ (g/kg) = 0.00008\ (GDD – 1455)^{2} + 151 \qquad [8']$$

The equation Sanderson (1992) developed to predict CP for Alfalfa stem (Equation 9, base temperature not reported) had an r^2 0.90 and RMSE 16.4:

$$CP\ (g/kg) = 0.000246\ (GDD)^{2} - 0.394\ (GDD) +262 \qquad [9]$$

It can be reformatted as Equation 9':

$$CP\ (g/kg) = 0.00025\ (GDD - 801)^{2} + 104.24 \qquad [9']$$

The number of developed equations for different species in the literature like the ones reported here are very limited. It is unpractical to develop one equation for each species concerned. Fortunately, it is found that forage CP varies more significantly between years than between species suggesting that environmental variables are more important than species differences in influencing CP levels (Hendrickson et al. 1997). Also, comparing the values of the constants, a trend could be found that if plant species are categorized. Different forage groups have different CP change patterns during the growing season. George and Bell (2001) using stage of maturity to predict annual range forage quality, found that filaree and bur clover started with higher CP levels than the annual grasses but CP declined more rapidly in filaree than bur clover and the annual grasses as the growing season progressed. The finding suggested forage CP could be predicted by function groups (for example: warm-season grasses, cool-season grasses, legumes, and forbs) instead of by individual species.

Animal intake preference

Hardison et al. (1954) reported the first quantative results showing the degree of selection by grazing cattle. Lofgreen et al. (1956) showed a small but consistent increase in TDN (Total Digestible Nutrient) due to selective grazing. It is generally accepted that cattle selectively grazing on forage to acquire better nutrient level than if offered with hay. Quirk and Stuth (1995) first defined the method to quantifying herbivore diet selection based on their preference. The method was adopted in PHYGROW later to predict animal intake. The PHYGROW model predicts available forage for animals by plant species. The diet selection sub-model allows a user to categorize animal preference for a particular plant species according to its phonological growth stage (i.e. Current year's growth during rapid growing, during declining growth, during dormancy, and during death). The model does this by assigning preference classes to each species at each growth stage as Preferred, Desirable, Undesirable, Emergency or Toxic (PHYGROW User Manual). From the PHYGROW source code, the rules for calculating plants growth stages for each species and thus their correspondence intake by a grazer are based on:

Rapid Growth Stage: previous leaf turnover $<$ previous growth

Declining Growth Stage: previous leaf turnover $>$ previous growth

Quiescence Growth Stage: previous leaf turnover = previous growth

Dead Growth Stage: previous growth

For a given herbivore, each type of forage is assigned to one of the four preferences categories at each growth stage. The four preference categories are: preferred (P), undesired (U), desired (D), and emergency (E). For each type of forage and grazer, with its particular growth stage and preference category, PHYGROW uses a set of rules to calculate its intake by the grazer.

GAN lab commercial fecal diet quality data

The second approach of the objectives requires analysis of the GAN lab commercial data to find direct correlation of fecal CP and GDD without using PHYGROW. GAN lab is using NIRS technology to predict animal dietary CP and DOM via scanning of fecal samples. When shipped to GAN lab, commercial samples will be dried and grounded and exposed to light energy. The reflectance is influenced by number and type of chemical bonds in the samples. Prediction equations are built and calibrated through known diet samples and paired animal feces. Equations developed to date appear to be highly reliable across a broad spectrum of forage types to predict dietary CP and DOM of free-ranging animals (Lyons and Stuth 1992). Currently over 1400 clients are using the GAN lab system in 48 states, which gives access to over 40,000 samples with their recorded collecting date, location, grazer, vegetation type, and predicted CP and DOM.

CHAPTER III

DEVELOPMENT OF A CATTLE DIET QUALITY MODEL USING TEMPERATURE DATA AND PHYGROW

Overview

For the purpose of developing a remotely accessible model to predict animal diet quality in replace of fecal Near Infrared Reflectance Spectroscopy (NIRS) analysis in the use of the Nutritional Balance Analyzer (NUTBAL) model for animal performance monitory and prediction, a new model was developed to predicted cattle diet quality based on the Phytomass Growth model (PHYGROW). Using the Growing Degree Days (GDD) concept, forage Crude Protein (CP %) estimation equations were developed for different species categories. PHYGROW cattle diet selection model was used to project cattle diet quantity of each available forage category. The CP quantity consumption by cattle was then calculated by the sum of weighted consumption of each consumed forage category's CP% based on their diet demand quantity. The diet CP% was calculated by dividing the weighted total of consumed CP by the total consumption of forage. The animal diet quality outputs of PHGROW were fed into NUTBAL to predict animal performance. A validation study was carried out to validate the equations and the performance of the PHYGROW – NUTBAL model system. The PHYGROW predicted standing crop was validated by clipping data. The new model predicted cattle diet quality correlated well with fecal NIRS analyzed data. The linked PHYGROW-NUTBAL predicted animal performance was validated by observed data.

The developed PHYGROW-NUBAL system performed well in predicting cattle performance. The study provided a valuable management tool for cattle production industry.

Introduction

Both the Phytomass Growth Model (PHYGROW) and The Nutritional Balance Analyzer (NUTBAL) model were developed by The Center for Natural Resource Information Technology (CNRIT) at Texas A&M University. PHYGROW predicts available forage for forage management purposes, while NUTBAL predicts animal performance for livestock management purposes.

PHYGROW is a hydrologic-based plant growth simulation model that predicts available forage under certain management criteria. It represents the complex interaction between available forage and numerous soil characteristics, plant community characteristics, grazing practices and weather data for a particular location (Stuth 1997). PHYGROW is a major component of the Livestock Early Warning System (LEWS) for monitoring nutrition and livestock health for food security of humans. LEWS is a sub-project within the Global Livestock Collaborative Research Support Program (GL-CRSP) currently being implemented widely by Texas A&M University in East Africa, Mongolia, Texas, New Mexico and Oklahoma.

NUTBAL predicts nutrient intake, requirements and balance of protein and energy for grazing animals based on the physical characteristics of the animals and their environment including available forage, forage quality, and weather condition. It also estimates body weight change, identifies the primary limiting nutrient (energy or protein), and reports dry matter intake and fecal output. The program has been used by commercial ranchers to detect forage nutrient deficiencies and identify cost- efficient supplemental strategies to meet production goals.

The original goal of PHYGROW is to predict forage availability for livestock and thus to manage their performance and production. The CNRIT system developed another model, NUTBAL, to complete the mission. The two models are tandem management tools for livestock production. The current version of PHYGROW only predicts the quantity of available forage, but knowing quantity alone is insufficient to determine livestock performance. The Near Infrared Reflectance Spectroscopy (NIRS) technology is used to predict animal diet quality from fecal analysis with resulting values used in NUTBAL to predict livestock performance (Lyons and Stuth 1992).

Because the lack of a forage quality prediction component in PHYGROW, the output can not be directly fed as an input to NUTBAL for a one step animal performance management system. A sub model that enables PHYGROW to predict diet quality will link the two models in one piece for managing livestock production.

The quantity and quality of consumed forage together determine the productivity of free ranging animals. When quantity of forage is not a limiting factor, diet quality plays the major role in animal production and performance (Lyons 1990). The ability to determine and predict animal diet quality is essential in managing supplemental feeding while controlling cost and production risk. Techniques like hand plucking of forage to mimic free-ranging animals' diets and the use of esophageal fistulated animals in determining animal diet quality are relatively low precision and labor intensive with a high sensitivity to bias (Kosi 2003). Forage crude protein (CP) and digestible organic matter (DOM) have been identified as being highly related to grazing animal forage intake and performance (Moore and Kunkle 1995). Ability to predict these dietary attributes will be of tremendous importance to free-ranging animal management. One popular method being used today to make such predictions is the Near Infrared Reflectance Spectroscopy (NIRS). The technology predicts animals' dietary CP and DOM by scanning of their fecal samples (Coleman et al. 1989; Stuth et al. 1991; Lyons and Stuth 1992). This gives relatively precise estimates but is time and costly consuming due to the physical collecting and analyzing process of fecal samples. Most of these techniques are used to predict animal dietary quality based on their past intake. Some models have been developed to predict available forage quantity a week or even a month ahead based on weather forecasting data (Stuth 1997), but little progress has been made in predicting the quality of the forage ahead of time.

The diet selection sub model in PHYGROW simulates animal's selective grazing behavior and predicts consumption quantity of each forage species at a given projected time point. We propose that coupled with some simple forage quality prediction equations this could be used to predict animal diet quality both in timely fashion and ahead of time. Many researchers found that Growing Degree Days (GDD) is a good predictor for predicting forage quality (Mitchell et al. 2001, Borreani et al. 2003b; and Hill et al. 1995). GDD is a simple temperature driven variable. The availability and easy access of weather forecasting data makes a GDD based model simple to use and suitable for diet quality forecasting. Most of the GDD predicting equations are species specific and different forage categories response differently to GDD accumulation. In order to develop a generalized model, some generalized equations need to be developed for categorized forage.

Model development and description

Forage CP

GDD calculates the heat unit accumulation above a minimum threshold temperature, often referred to as the base temperature. The accumulation equation commonly used is:

$$GDD= (T_{max}+T_{min})/2-T_{base} \qquad [10]$$

where T_{max} is the daily maximum temperature, T_{min} is the daily minimum temperature and T_{base} is a species specific base temperature required for growth.

Seven CP prediction equations are found in literature for different species (Mitchell et al. 2001; Smart et al. 2001; Hill et al. 1995; Borreani et al. 2003a; Sanderson 1992). We rewrite them in the standard quadratic form of:

$$CP = a\,(GDD\text{-}b)^{2} + c \qquad [11]$$

where a, b and c are constants and their meaning will be further discussed.

All the constants of rewritten equations are summarized in Table 1. In the quadratic graph of the CP (g/kg) = a (GDD-b) ^{2}+ c, 'a' is the curve factor determines the slope of the curve, while coordinate (b, c) determines the X and Y axis values for the lowest coordinates on the graph when 'a' is negative. In Table 1, 'a' for all first 4 equations for warm season grasses are all about 0.0001, which means the rate of CP decline with increasing GDD might be similar for these warm season species. We hypothesis that coefficient 'a' for warm season species is 0.0001. To test, we also hypothesize the coefficients 'a' for cool season grasses is 0.00016 and for legumes is 0.00025.

Table 1. Literature summary of the reformed GDD as a predictor for CP equations.[1]

Source	Species	a	b	c	T_{base} (ºC)
Mitchell et al. 2001	Switchgrass	0.00010	1500	38.85	10
Mitchell et al. 2001	Big bluestem	0.00010	1550	37.07	10
Smart et al. 2001	Big bluestem	0.00006	1610	64.47	5
Smart et al. 2001	Big bluestem	0.00009	1373	44.21	5
Hill et al. 1995	Tall fescue	0.00016	1122	N/A	5
Borreani et al. 2003a	Sulla	0.00008	1455	151.00	5
Sanderson 1992	Alfalfa	0.00025	801	104.24	5

[1] a, b and c are coefficients in the format of CP (g/kg) = a (GDD-b) ^{2} + c, T_{base} is the base temperature for calculating GDD.

Comparing the equation's coordinates (b, c) from Mitchell et al (2001) which is (1500, 38.85) to its graph in Figure 1 which is around (1550, 40), coefficient b is highly possible to be the highest GDD for a given plant species at the stage of quiescence, and coefficient c is the lowest CP upon quiescence for warm season and cool season grasses. Figure 2 is a CP/GDD graph for a legume which shows the lowest point is roughly (700, 120). The finding correlate to the magnitude of Alfalfa's lowest coordinates (801, 104.24) in Table 1, thus the hypothesis for coefficients b, c of warm season and cool season grasses also appear to hold good for legumes.

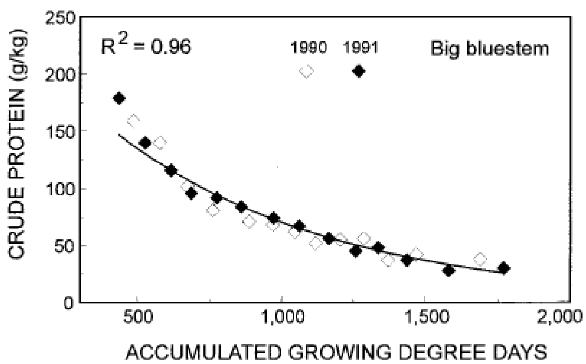

Figure 1. Big bluestem CP in relation to GDD. (Mitchell et al. 2001)

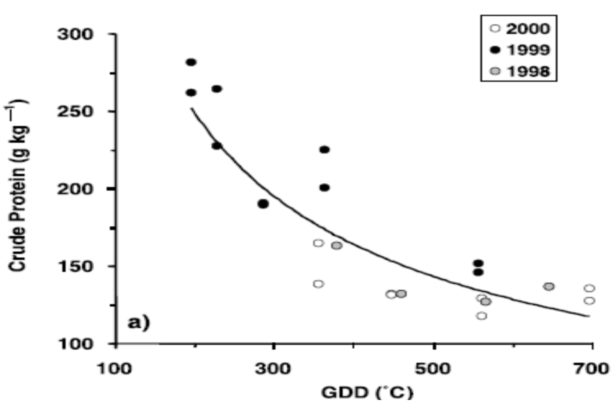

Figure 2. Legume sainfoin (*Onobrychis viciifolia*) CP in relation to GDD. (Borreani et al. 2003b)

In summary, we propose that the equations for predicting forage quality are:

Warm season grasses: $CP = 0.0001(GDD - GDD_{max})^2 + CP_q$ [12]

Cool season grasses: $CP = 0.00016\ (GDD - GDD_{max})^2 + CP_q$ [13]

Legumes: $CP = 0.00025\ (GDD - GDD_{max})^2 + CP_q$ [14]

where GDD_{max} is the maximum GDD for a given species in a growing season and CP_q is the minimum CP level for a species upon quiescence.

Animal diet selection in PHYGROW

Besides the proposed forage quality prediction equations, how animal actually consume different species determines the consumed diet quality. The rules of the later are specified in PHYGROW's animal diet selection sub-model. In PHYGROW Manual, for a given herbivore, each type of forage is assigned to one of the four preferences categories at each growth stage. The four preference categories are: preferred (P), undesired (U), desired (D), and emergency (E). For each type of forage and grazer, with its particular growth stage and preference category, PHYGROW uses the following rules to calculate its intake by the grazer.

PHYGROW assumes herbivores avoid consuming emergency plants. For the other three categories, it calculates a "factor", represents the percentage of forage in each category the grazer would consume during unlimited supply, for the grazer/forage pair, e.g. preferedFactor, undesirableFactor, desirableFactor based on:

preferedFactor = 1 - exp (-3.65 * pf / tf) where pf is the total available preferred forage, and tf is the total available forage

undesirableFactor = 0.031971 * exp(2.89 * uf / tf)

where uf is total available undesirable forage

desirableFactor =1.0 - undesirableFactor- preferedFactor

Then, PHYGROW calculates the "extra demand", which indicates whether herbivor is grazing according to its preference factors, the following rules apply:

pd = max(0, demand * preferedFactor - pf)

ud = max(0, demand * undesirableFactor - uf)

dd = max(0, demand * desirableFactor- df)

extraDemand= dd + ud + pd

where pd is preferred forage demand, ud is undesired forage demand, and dd is desired forage demand; pf, uf and df are total available preferred forage, total available undesirable forage and total available desirable forage respectively.

Then if the extra demand = 0, individual intake of different plants is calculated as:

For preferred forage: pi=demand * desirableFactor

For undesirable forage: ui=demand * undesirableFactor

For desirable forage: di=demand * desirableFactor

where pi, ui and di are intake for preferred, undesired and desired forage respectively.

If the extra demand > 0, the individual intake of different plants is calculated as:

For preferred forage: pi=demand*pf/tf

For undesirable forage: ui=demand * uf/tf

For desirable forage: di=demand * df/tf

where pf, uf, df are the total available preferred, undesirable, and desirable forage and tf is total available forage.

This animal diet selection sub-model in PHYGROW coupled with the forage quality prediction equations proposed before provides the necessary components to calculate animal diet CP.

Animal diet CP

PHYGROW is designed to calculate a grazer's intake for a particular forage species. PHYGROW will generate a database for a grazer that is using a particular forage community as following example in Table 2:

Table 2. A PHYGROW grazer diet selection example.[1]

Species	Growth Stage	Preference	Intake	Intake CP
1	Rapid growth	Preferred	pi	pi*CP1
2	Dead	Undesirable	ui	ui*CP2
3	Declining growth	Desirable	di	di*CP3
4	Quiescence	Emergency	0	0

[1]CP1, CP2 and CP3 are predicted CP for species 1, 2 and 3 respectively using the proposed forage quality model.

Now, the diet quality model for a grazer which is grazing on a pasture consisting of only the four species as in Table 2 is proposed to be:

$$I_{cp}=piCP1+uiCP2+diCP3 \qquad [15]$$

where I_{cp} is the total intake CP value

Animal diet DOM

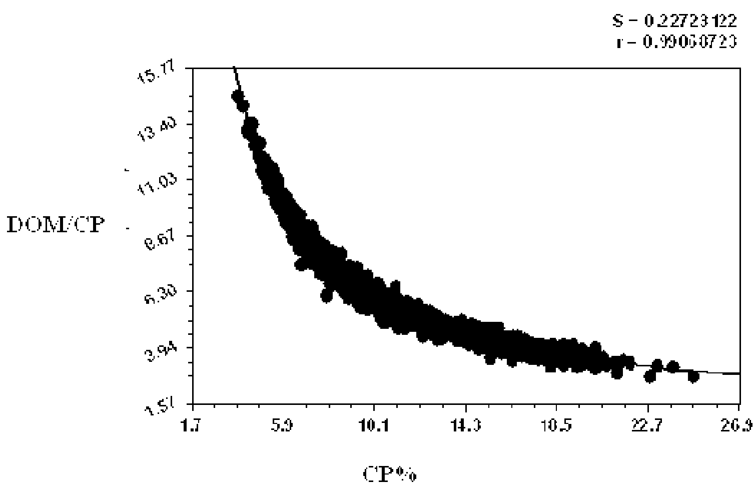

Figure 3. Fecal NIRS analyzed ratio of DOM/CP in relation to CP (%).

A logistic model has been developed to regress the ratio of DOM/CP (y) on CP (x) using datasets from GAN lab's commercial fecal NIRS data (Fig. 3). The dataset contains 13,000 samples from locations all across U.S. Each sample was prepared under the standard procedure described by Lyons and Stuth (1991). DOM and CP here in the regression are predicted by these samples using the NIRS technology. The model is:

$$y = a / (1 + b\, e^{-cx}) \qquad [16]$$

with standard error 0.227 and r^2 of 0.99, and a = 1.52, b = - 1.00 and c = 0.029 (Figure 3). Therefore we calculate diet DOM from established CP by using the following equation:

$$I_{dom}=1.52\ I_{cp} / (1- e^{-0.029\ Icp}) \qquad [17]$$

where I_{cp} is diet CP and I_{dom} is diet DOM.

Model validation

A 2-year grazing trial was carried out to validate the intake quality models for a mixed plant community. Three 6-month old Angus steers in 2005 with average weight 500 ± 35 lbs and three 6-month old Angus heifers in 2006 with average weight 432 ± 23 lbs were put on a 6.7 acre native range paddock with initial standing crop of 3684 ± 43 lbs/acre near Eastwood airport, College Station, TX (latitudes 30.5667 N, Longitudes -96.3667 W), owned by the Department of Ecosystem Science and Management, Texas A&M University. This area is characterized as Texas Post Oak Savannah (Gould and Box 1958) dominated by warm-season, perennial grasses with sporadic woody overstory. The grazing trial lasted from August 01 to December 25 in 2005, and from April 15 to September 30 in 2006. Before the study, the pasture had not been grazed for 2 years. The cattle solely relied on the forage in the pasture. No supplement feeding was provided. Fecal samples were collected weekly from each animal at approximately the same time of the day. Samples were placed in polyethylene zipper-seal bags and dried in a forced-air oven at 60 ºC for 48 hours. Dried samples were grounded in a Udy cyclone mill to pass a 1-mm screen to ensure uniform particle dimension for improved precision of NIRS results (Norris et al. 1976). Samples then coolled 1 hour in a desiccator prior to NIRS analysis (Lyons and Stuth 1992) NIRS predicted CP and DOM data were obtained. The weights of each animal were recorded every 14 days at approximately the same time of the day each time (Table 3). Mean observed weights of the three heifers in 2006 started from 432 lbs to 615 lbs with an average daily gain range of 0. 6 lbs to 2.7 lbs (Table 3). Forage were clipped every month to obtain the total crop yield and compared with PHYGROW predicted crop yield to validate the PHYGROW function. The PHYGROW-NUTBAL model predicted weights in 2006 are compared with observed weights and NIRS fecal data predicted weights.

Table 3. Observed weights in lbs of three heifers in 2006, range area.

date	Animal 1	Animal 2	Animal 3	Mean ± SE	AverageDailyGain
5/1	407	438	452	432 ± **23**	N/A
5/18	448	454	486	463 ± **20**	2.2
6/1	474.3	470	503	482 ± **18**	1.4
6/15	491	495	517	501 ± **14**	1.3
6/29	503	508	547	519 ± **24**	1.3
7/13	511	535	570	539 ± **30**	1.4
7/27	525	541.5	575	547 ± **25**	0.6
8/10	533	566	589	563 ± **28**	1.1
8/24	550	574	606	577 ± **28**	1.0
9/7	587	610	648	615 ± **31**	2.7

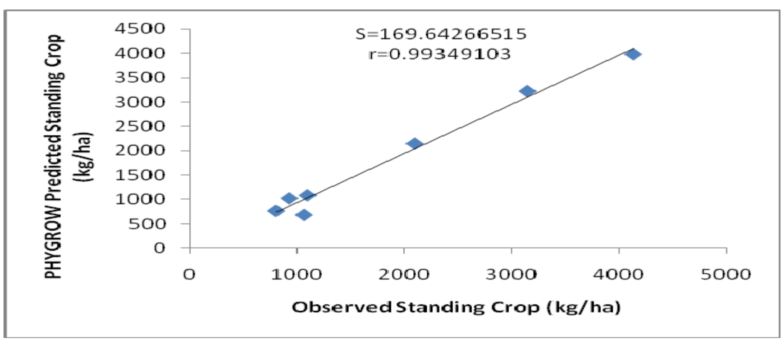

Figure 4. Comparison of PHYGROW predicted available forage over clipping data.

A good relationship (y=-41.51+0.99x) of PHYGROW predicted standing crop over clipped data with an r^2 vale of 0.99 and standard deviation of 169. 64 kg/ha validates PHYGROW is efficiently predicting standing crop at the experiment site (Fig. 4). The results ensure the use of PHYGROW predicted forage quantity and animal diet selection sub-model for further simulation.

The equations of the GDD model predicted cattle diet CP over fecal samples predicted diet CP for 2005 and 2006 are y=2.15+0. 62x and y=1.82+0.80x respectively. They both give a positive intercept, 2.15 for 2005 and 1.82 for 2006. The r^2 value for 2005 is 0.78 and for 2006 is 0.82 indicates the correlations are significant (Fig. 5 and Fig. 6). P value for testing the two year interaction of intercept and slope are <0.0001 and 0.0409, respectively, indicating there is no significantly consistent trends for prediction bias between the two years. The 2 year (2005 and 2006) pooled equation is y=1.57+0.81x with a positive intercept and a slope less than 1. The r^2 value of 0.84 indicates the correlation is significant (Fig. 7). P values are all less than 0.0001 for the test of slope = 1 and intercept = 0 indicates prediction biases are insignificant (Table 4).

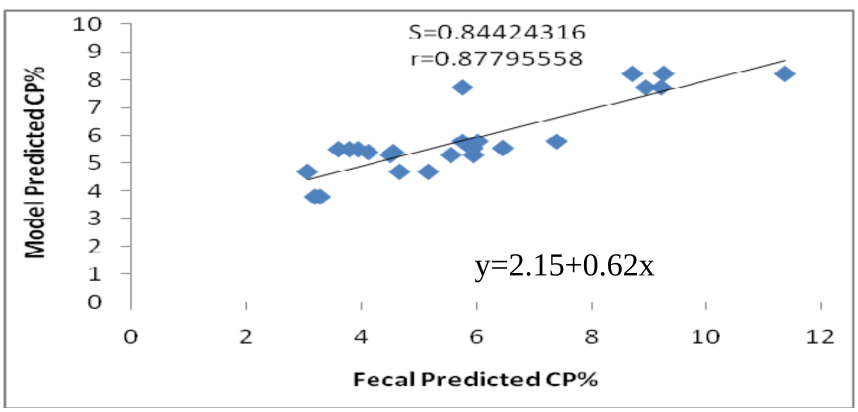

Figure 5. Comparison of new model predicted cattle diet CP% over fecal sample predicted cattle diet CP% for 2005.

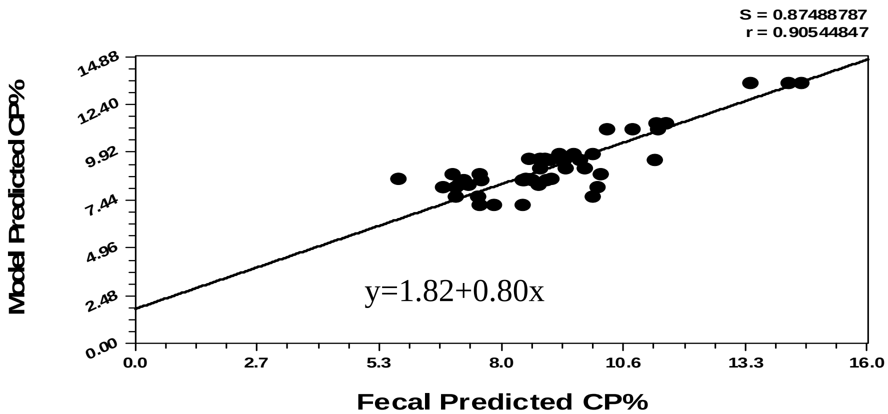

Figure 6. Comparison of new model predicted cattle diet CP% over fecal sample predicted cattle diet CP% for 2006.

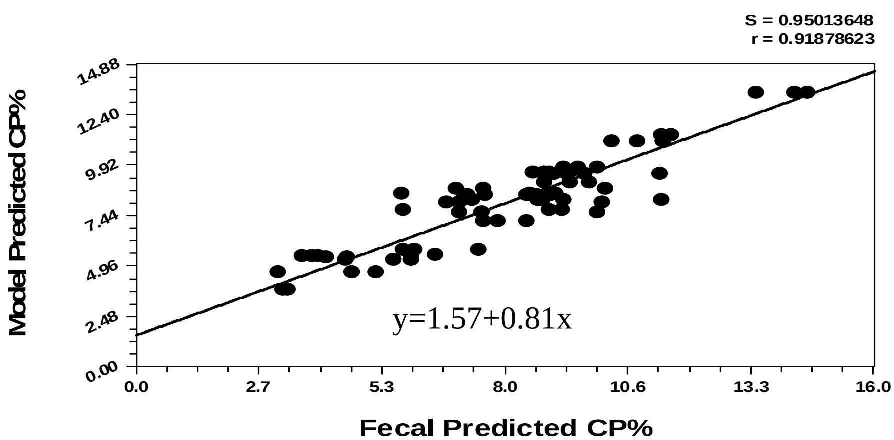

Figure 7. Comparison of new model predicted cattle diet CP% over fecal sample predicted cattle diet CP% for 2005 and 2006 combined.

Table 4. Validation of the diet CP quality prediction model by fecal NIRS predicted CP in 1995, 1996 and 2 year combined.[1]

Validation Source	Intercept	Linear Coefficients	r^2	Root MSE
2005	2.15(<.0001)	0.62(<.0001)	0.78	0.69
2006	1.82(<.0001)	0.80(<.0001)	0.82	0.82
2 year combined	1.57(<.0001)	0.81(<.0001)	0.84	0.94

[1]n= 25 (2005), 73 (2006), and 98 (2 year combined), Parenthetic values following intercepts and linear coefficients are the P values for the intercept 0 and slope 1 tests respectively.

NIRS fecal data predicted weights versus observed weights curve give a straight line ($y=0.23+0.81x$, Fig. 8) with interception of 0.23 ($r^2=0.94$, $s=0.16$). This validates the NUTBAL model running well for the case.

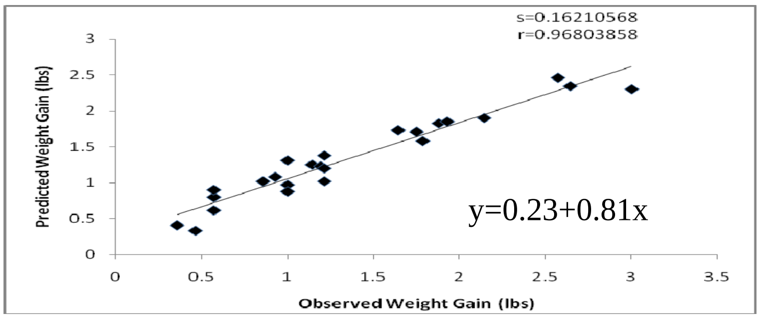

Figure 8. NIRS fecal data predicted weights over observed weights.

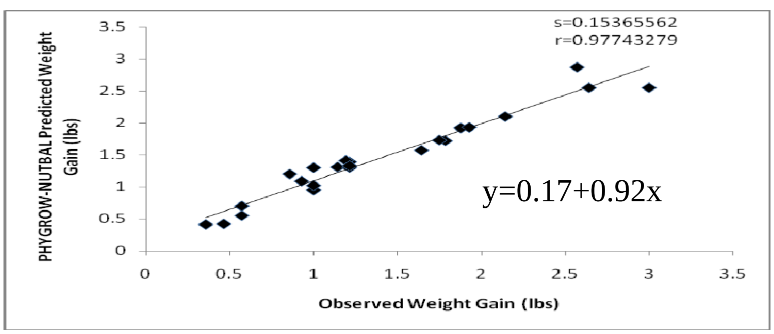

Figure 9. PHYGROW-NUTBAL predicted weights over observed weights.

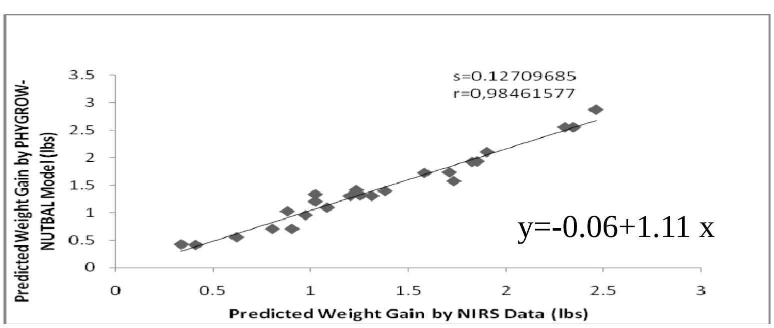

Figure 10. PHYGROW-NUTBAL predicted weights over NIRS fecal data predicted weights.

Both PHYGROW-NUTBAL predicted weights versus observed weights curve ($y=0.17+0.92x$, $r^2=0.96$, $s=0.15$, Fig. 9) and PHYGROW-NUTBAL predicted weights versus NIRS fecal data predicted weights curve ($y=-0.06+1.11x$, $r^2=0.97$, $s=0.13$, Fig. 10) display a straight line with interceptions of around 0 (-0.06, and 0.17).

Discussion

Validation of the model predicted cattle diet quality by fecal NIRS predicted cattle diet quality indicates the developed model can be used to predict cattle diet quality to replace the fecal NIRS approach. One would find it useful in making management decisions regarding large scale grazing land where fecal NIRS method is difficult to apply or when cattle dietary information needs to be obtained immediately which Fecal NIRS method could not offer. The validation of the developed cattle diet quality model and its application in PHYGROW-NUTBAL system indicates the model could be used to link PHYGROW and NUTBAL together to provide integrated decision supporting system for grazing cattle management.

The source of the error may come from the three step modeling process: the error from PHYGROW modeled standing crop; the error from forage quality predictions; and the error from animal diet quality selection sub-model in PHYGROW. Further studies should focus on increasing the accuracy of the model by decreasing all the three sources of error. Because there is no other economically alternative tool available to give better estimates of animal diet quality, the developed model is thus an encouraging first step towards development of an accurate yet economically available tool assisting management decision making. It also provides a foundation for future application study for a variety of animal kinds.

CHAPTER IV

A SIMPLE TEMPERATURE DRIVEN CATTLE DIET QUALITY MODEL

Overview

In searching for a simplified model to predict cattle diet quality, Grazing Animal Nutrition lab (GAN lab) commercial fecal Near Infrared Reflectance Spectroscopy (NIRS) analyzing data for Major Land Resource Area 42 (MLRA 42) is used to analyze the relationship between Growing Degree Days (GDD) and cattle diet Crude Protein (CP%) and Digestible Organic Matter (DOM %). Eight ranches within the region were randomly selected for analysis. Fecal CP and DOM for each ranch is regressed over GDD for that ranch and its species composition. Repeatable high quality regressions are reported for CP and GDD for these ranches. A simple temperature based model then is developed to predict cattle diet quality for the regional use for native pasture with no supplement feeding. Data from another region (MLRA 116B) and a controlled grazing study carried out in College Station, TX, were used to validate the application of the relationship over different regions. The study showed Using GDD to predict cattle diet quality is a valuable tool, but region specific relationships need to be developed.

Introduction

Knowing diet quality is essential for effective cattle production from rangelands because it reveals the quantity and quality of supplement feeding requirements. One of the popular tools currently available for predicting cattle diet quality is fecal Near

Infrared Spectroscope (NIRS) profiling (Stuth et al. 2003b; Lyons and Stuth 1992; Coates 1998; Gibbs et al. 2002; Gallagher 1990; Keating 2005). Although it is a fairly quick and accurate method, it does require time and financial investment. When there is a need to consistently monitor diet quality for grazing animals over a considerable time for distant locations or over large areas, or obtain results rapidly, NIRS fecal analysis may be neither logistically or economically feasible.

A model that can predict cattle diet quality in remote locations is very valuable. However, little research has been done to address this need. This may be partly because of the difficulty of modeling the complex nature of herbivore-forage interaction with respect to diet selection behavior.

A model has been developed to predict cattle diet quality based on a forage production predicting model (PHYGROW) and one newly developed plant CP prediction model. PHYGROW is a hydrologic-based plant growth simulation model that predicts standing crop under certain management criteria. It represents the complex interaction between numerous soil characteristics, plant community characteristics, grazing practices and weather data for a particular location (Stuth et al. 2003b). The animal diet selection sub model within PHYGROW enables it to simulate the kind and amount of forage being selectively consumed by certain animal and thus calculate the available forage for a particular kind of animal. The diet selection sub model places plant species into five preference categories (Preferred, Desirable, Undesirable, Toxic and Emergency) and computes the proportion of each preference class in the diet. The animal preference of a plant species can be assigned by a user according to phonological stage: fast growth, declining growth, quiescence, dormancy and dead (Quirk and Stuth 1995). The plant CP prediction model I developed was using Growing Degree Days (GDD) to predict plant CP content. The relationship of plant CP and GDD is well documented (Mitchell et al. 2001; Borreani et al. 2003a; Hill et al. 1995; West et al. 1991). PHYGROW produces available forage quantity by species; the animal diet selection sub model in PHYGROW projects how animals selectively graze each species. By scaling predicted species specific plant CP by the amount each is being grazed, animal diet CP proportional content of each species in their diets and thus the total CP content are predicted.

The GDD model developed for predicting diet quality is a fairly accurate tool that can be applied in remote locations. When used with PHYGROW, trained professionals are needed and the initial setup requires extensive sampling on the physical location. In an effort to develop a further simplified model to predict diet quality, and inspire by the idea that GDD is the driving force of plant quality and cattle often attempt to obtain the best diet quality available from a forage community, the direct relationship between GDD and cattle diet CP is assessed.

Repeatable relations between GDD and cattle diet CP is highly valuable in remotely predicting cattle diet quality, especially on landscape level where no other alternative method is economically available. The attractive feature of temperature driven models is that it is useful not only for predicting current cattle diet quality but for projecting future diet quality based on forecast weather data. After baseline information, (forage community composition, dominated species and base temperature), is collected from field survey or from similar proximate areas, the remaining cost of running the model will be the cost of acquiring temperature data from government or commercial weather data storage and forecasting centers. The model developed here is a low cost, easy to access and convenient tool for grazing cattle management.

We regressed animal diet CP over GDD for Major Land Resource Area 42 (MLRA 42, Figure 11) from GAN lab commercial dataset. A given MLRA usually has similar soil, geographic features and thus plant community composition. The analyses are done at the individual ranch scale and data combined to assess the correlations. Data for MLRA 116B and a controlled grazing study in College Station, TX were also analyzed to look at the applicability of a universal relationship. Diet DOM is also regressed over GDD. Since a good relationship between diet DOM/CP over CP were found based on GAN lab data (Fig. 3), the two methods of predicting DOM from GDD and predicting DOM from CP are compared.

Data and methods

The dataset used to develop the relationship was obtained from the GAN lab. Information about each sample in this dataset includes ranch name from which fecal sample was collected, date the fecal sample was collected, latitude and longitude of the collection location, kind of animal, vegetation type at the location, GAN lab predicted diet CP% and DOM%.

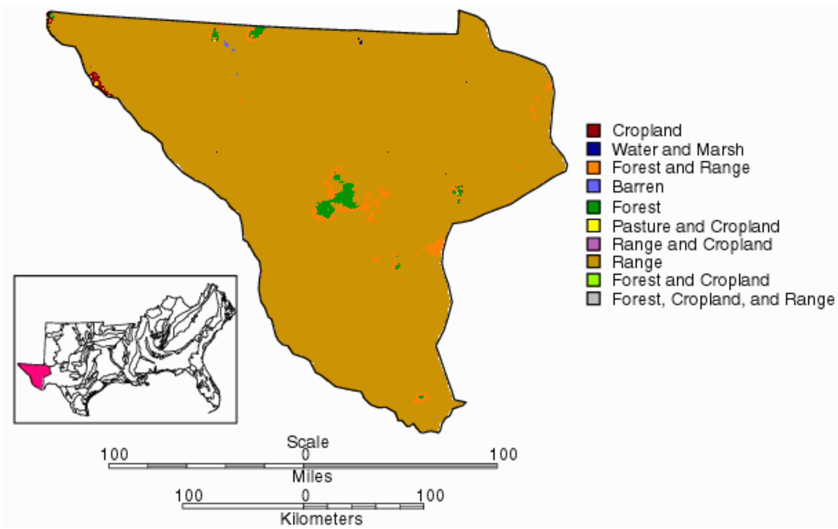

Figure 11. Map of MLRA 42 (Southern Desertic Basins, Mountains, and Plains).

The subset randomly chosen for analysis was MLRA 42 (Fig. 11), Southern Desertic Basins, Plains, and Mountains (USDA NRCS 1997). This region comprises 13 million ha and extends from Texas northwest to include portions of Arizona and New Mexico. Annual average precipitation in the area ranges from 203mm to 262mm. The average annual air temperature is about 16 °C. Frost free season exceeds 200 days and extends from April 1 to November 1. The temperature regime and rainfall distribution favor the growth of warm-season perennial plants on the site. Spring moisture conditions are only occasionally adequate to cause significant growth during this period of the year.

Samples collected during winter months were eliminated to avoid distortion due to possible supplement feeding. GDD were computed by subtracting a base temperature for plant growth from daily average temperature. The equation used to determine GDD was:

$$GDD= (T_{max}+T_{min})/2-T_{base} \qquad [18]$$

Base temperature of 10 ºC was used because the dominated plant species in this region are warm season grasses. We regressed 7 ranches for their fecal CP over GDD using CurveExpert 1.37. These ranches were selected because they are cattle operations that match the study subject, and they represent native rangeland to eliminate the possibility that improved pasture could have very different forage complex and thus with different base temperature than the one we selected to calculate GDD. The curves which provided the highest r^2 value, i.e, best fit, are reported. All the data then pooled to regress CP over GDD for an overall fit. For the quadratic fit relations, the equations were converted to the standard form of Equation 2 to compare their similarity,

$$CP = a (GDD-b)^2 + c \qquad [2]$$

where a, b and c are constants. Coordinates (b, c) represents the highest or lowest point on the quadratic graph of the equation and a represents the slope of the graph.

A different region, MLRA 116B, was selected to validate the model. This area is predominantly in southwest Missouri and extends for a short distance into the northeast corner of Oklahoma and southeast Kansas. It makes up about 352.01 square miles (USDA NRCS 1997). Elevation ranges from 200 to 500m. Average annual precipitation is 975 to 1,225 mm. Maximum precipitations is mainly in spring and early in summer, and the minimum is in midsummer. Average annual temperature is -13 to 16°C. Average freeze-free period is -180 to 200 days. This area supports savanna vegetation. Dominant grassland species are Big bluestem, little bluestem, indiangrass, and switchgrass.

A grazing trial was also carried out to validate the application of the model over other regions. Three 6-month old Angus heifers in 2006 with average weight 432 ± 23 lbs were put on a 6.7 acre native range paddock with initial standing crop of 3684 ± 43 lbs/acre near Eastwood airport, College Station, TX (latitudes 30.5667 N, Longitudes -96.3667 W), owned by the Department of Ecosystem Science and Management, Texas A&M University. This area is characterized as Texas Post Oak Savannah (Gould and Box 1958) dominated by warm-season, perennial grasses with sporadic woody overstory. The cattle solely relied on the forage in the pasture. No supplement feeding was provided. Fecal samples were collected weekly from each animal at approximately the same time of the day. Samples were placed in polyethylene zipper-seal bags and dried in a forced-air oven at 60 ºC for 48 hours. Dried samples were grounded in a Udy cyclone mill to pass a 1-mm screen to ensure uniform particle dimension for improved precision of NIRS results (Norris et al. 1976). Samples then coolled 1 hour in a desiccator prior to NIRS analysis (Lyons and Stuth 1992) NIRS predicted CP and DOM data were obtained. The diet CP was then regressed over GDD with base temperature of 10 ºC.

Results

The regressions of CP% over GDD repeatedly gave good quadratic relationships for all the seven ranches (Figure 12:A-G). Coefficients of determination range from 0.52 to 0.99 (Table 5), and standard deviation ranges from 0.49 to 1.93 (Table 5). All the ranches combined for MLRA 42, a general quadratic regression could be developed (Fig. 12: MLRA 42) with coefficient of determination of 0.64 and standard deviation of 1.67. Regression equations for each ranch and combined are summarized in Table 5 and the coefficients a, b and c in the format of Equation 2 are also summarized in Table 5. Coefficients a represents how fast the diet CP increase or decrease, coordinate (b, c) represents the highest CP and the GDD when the highest CP occurs. Comparing coefficients a, b and c for the seven ranches, the highest diet CP is ranging from 9. 65 to 12.57 and the GDD at which when the highest CP occurs is ranging from 1095.43 to 1890.73 (Table 5).

Table 5. Relationships between CP and GDD for MLRA 42.

Ranch	Equations	S	r^2	a (e^{-06})	B	c
A	$2.44+0.01x-0.000004x^2$	1.74	0.85	-3.95	1595.60	12.49
B	$0.21+0.01x-0.000004x^2$	1.39	0.92	-3.54	1890.78	12.45
C	$3.23+0.01x-0.000003x^2$	2.06	0.52	-3.24	1407.45	9.65
D	$3.38+0.01-0.000003x^2$	1.90	0.72	-3.16	1654.12	12.03
E	$3.69+0.01-0.000002x^2$	2.05	0.99	-2.23	1841.16	11.25
F	$0.18+0.01-0.000004x^2$	0.49	0.99	-4.33	1520.41	10.19
G	$3.55+0.02-0.000008x^2$	1.93	0.60	-7.52	1095.43	12.57
Combined	$3.84+0.01-0.000003x^2$	1.67	0.64	-2.59	1727.00	11.58

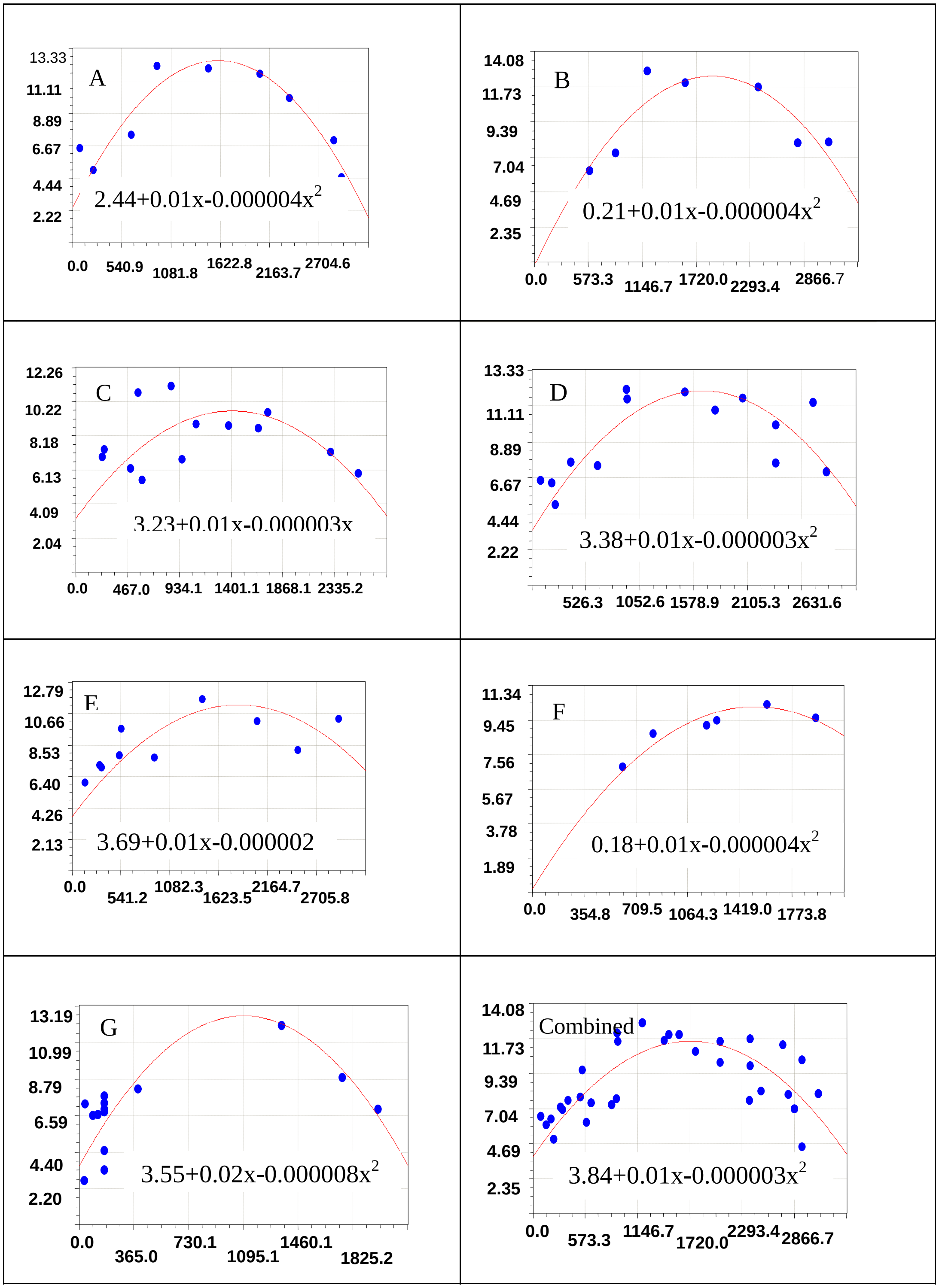

Figure 12. Relationship between CP% (Y axis) and GDD (X axis) for the seven ranches (A-G) and the combined in MLRA 42.

The regressions for DOM % over GDD have high r^2 values but relationships significantly differ among sample locations (Table 6). A logistic model has been developed to regress the ratio of DOM/CP on CP (%) using datasets from GAN lab's commercial fecal NIRS data. The model is:

$$y = a / (1 + b\, e^{-cx}) \quad [16]$$

Once CP is determined, using the relation of DOM/CP over CP would be a better way to predict diet DOM values than directly predict DOM from GDD (Fig. 3).

Table 6. Relationships between DOM and GDD for MLRA 42.

Ranch	Equations	S	r^2
A	$y=(0.02+60.49x^{0.70})/(4.12+x^{0.70})$	3.13	0.99
B	$y=(2800.64+59.23x^{2.69})/(4000919.00+x^{2.69})$	3.05	0.99
C	$y=21.54+0.18x+0.0002x^2+\ldots$	9.58	0.58
D	$y=(0.02+61.36x^{0.68})/(4.70+x^{0.68})$	2.15	0.98
E	$y=58.05(1-\exp(-0.02x))$	0.49	0.99
F	$y=63.04(1-\exp(-0.13x))$	1.09	0.99
G	$y=-1.11e^9x/(1-1.91e^7x+947.68x^2)$	1.93	0.60
Combined	$y=71.45x^{0.10}/(0.41+x^{0.10})$	3.66	0.80

CP data are also regressed over GDD for the validation site MLRA 116B (Fig. 14) and for the controlled study in Range Area (Fig. 13). Different equations were found which are not consistent with the quadratic equations found for MLRA 42 although it has good correlation (r^2=0.81, 0.77; Fig. 13, and Fig. 14). This indicates there may be different relationships for different regions.

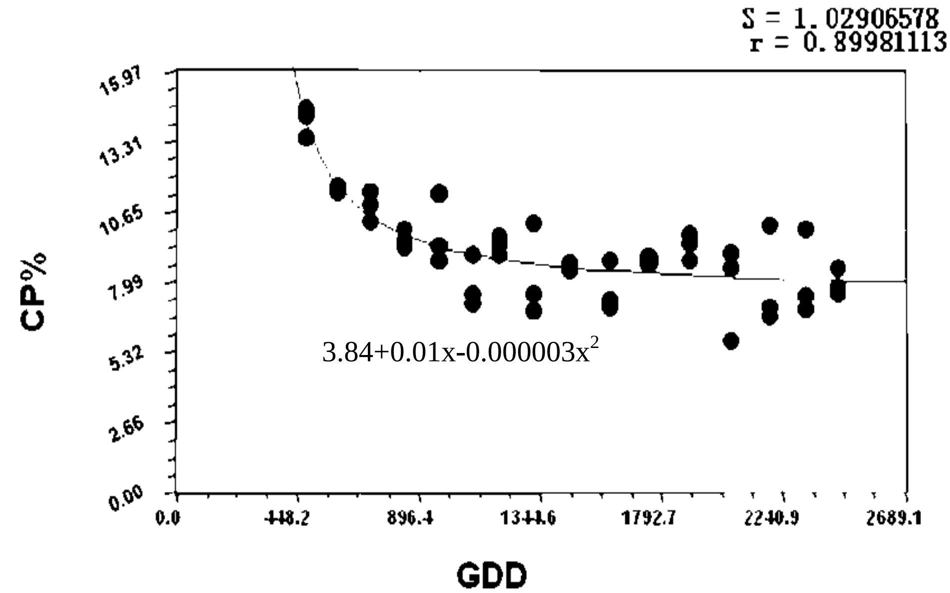

Figure 13. Relationship between CP% and GDD for range area.

*Model: $y=(a*b+c*x^d)/(b+x^d)$, with a=0.01, b=-1210.16, c=7.55 and d=1.27

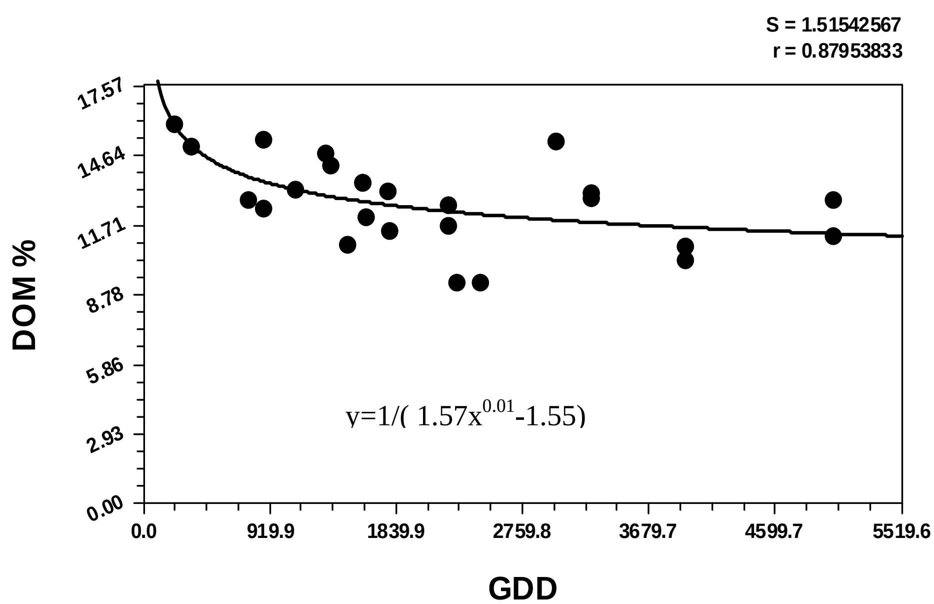

Figure 14. Relationship between CP% and GDD for MLRA 116B.

Discussion

With no other economically sound alternative methods for predicting cattle diet quality over landscape scales, the relations could be used commercially for predicting cattle diet quality under the following conditions: No supplement feeding is added, cattle only or dominated herd composition, light to medium grazing pressure.

One prediction equation could be developed for one geographic region with similar climate and vegetation community. The smaller the scale of the application area is, the higher the accuracy. Depending on the forage community and climate, different landscape should have very different relationships. Fortunately, databases like the one of GAN lab are available for diet quality information all across America. Landscape relationships between diet quality and GDD could be developed remotely based on these data. Once regional common relationships are developed, coupled with weather predicting information system, regional or even national real time and forecasting livestock diet quality map could be developed.

These relations are applicable under the situation of free ranging animals with unlimited or minor restrained supply of forage. Because the fraction of diet quality either supplied by supplement feeding or restrained by limited forage supply are relatively easy to measure, future research could be expected for successfully developing an advanced model for extent use under these situations.

CHAPTER V

SUMMARY AND CONCLUSION

Two different approaches were taken to predicting cattle diet quality. The first approach, which will hereafter be referred as the integrated model, incorporated GDD based forage quality prediction equations with PHYGROW and its animal diet selection sub model to predict animal diet quality. The other significant outcome of the approach is that PHYGROW and NUTBAL are now could be linked together using the diet quality prediction method instead of NIRS fecal analysis to provide a more economic and rapid tool for rangeland grazing management. The second approach, which will hereafter be referred as the simple model, is a simple temperature driven prediction model that predicts cattle diet quality directly from GDD.

For predicting cattle diet quality, both approaches discussed here have broader applications than NIRS fecal analysis, hand plucking of forage to mimic free-ranging animals' diets and the use of esophageal fistulated animals in determining animal diet quality. The most significant advantage of the developed models is that they can be used remotely. After the initial forage sampling and set up of PHYGROW, the integrated model could be used to predict cattle diet quality just with the added input of weather data, which could be obtained from various resources without ongoing sample collection on the physical location. The simple model only has air temperature as its input and a predetermined plant growth base temperature. Once the plant community composition is been assessed and the base temperature for plant growth is determined, with empirical data record for NIRS fecal predicted cattle diet quality, a equation directly link cattle diet quality to GDD could be developed for the location concerned. And ongoing cattle diet quality could be predicted by feeding remotely accessible temperature data in the equation. The second advantage of the two developed models is their low maintenance cost feature. Compared to other methods which require extensive ongoing labor, time and financial investment, the only maintenance cost of the two models is the cost to acquire weather data. The third advantage is that the models are feasible to be used in managing large scale land units. The other three techniques are all suited for small scale production management because of the enormous cost they associated to generate information over large landscape scale.

The two models are similar in their required inputs (weather data), fundamental structure (GDD driven) and accuracy. Their applications should be differentiated, however, to optimize their use. The integrated model involves use of PHYGROW and its setup which requires initial forage sampling. The information of plant community, its composition and relative abundance, must be obtained beforehand, thus suited for medium to small scale application. The simple model doesn’t need any sampling once equations are initially set up through existing data like GAN lab dataset, thus could be used in all scales. Since the integrated model has more information of the study areas like the plant community, the grazing pressure, the management rules applied, its application will be more general than the simple model. The simple model has limited application when the study area is heavily grazed or supplement feeding is present. The integrated model, on the other hand, could be used with various grazing pressure and whether or not supplement feeding is present. Although both models are developed for cattle only operation, the integrated model can be easily converted for other grazing animals or mixed herd operation then the simple model. Since the forage quality and animal selection are two separate modeling steps in the integrated model, and the forage quality modeling step dose not involve any variables for the grazing animal. All that is need to apply it for a new kind of animal is the assignment of different animal preference values in the animal selection step will convert the model for a new kind of grazing animal or even a mixed herd. Theory behind the simple model is like a black box. Cattle are the black boxes. How they selectively grazing to get the best out of the resources and how the composition of the forage community affects their intake and digestion are unknown. Since cattle are the mystery here, conversion of the model for other grazing animals will be not feasible. Although one can develop equations for other kinds of animals based on their fecal analysis data, what worked for cattle may not work for other kinds of animals.

This is a pioneer research in predicting cattle diet quality indirectly other than fecal NIRS analysis. The two developed models provided a rapid, economically sound, remotely accessible tool for predicting cattle diet quality. Application of the models will provide the general users of the cattle production industry an excellent way to calculate production cost and thus better managing their cost and revenue. Integrated with

PHYGROW and NUTBAL, animal nutritional requirements and performance could be predicted. Profound influences in the industry are expected to happen once the models are widely adopted.

The research also provided a framework and foundation for future work. One direction of further research will be to develop applications for different grazing animals using the same frameworks. The other direction is to increase the accuracy of the integrated model by looking at the three modeling steps separately.

The research focused on application within ranches or regions sharing uniform environment. Since the simple model requires fewer inputs and the necessary inputs are relatively easy to acquire, an amazing potential application for the simple model is to be used to develop diet quality map for across regions or even the whole US. This diet quality map application requires baseline data of regional plant growth base temperature to calculate GDD, the information could be obtained through field survey, literature data or approximation from surrounding regions or regions with similar plant community and environment. Since GDD and diet quality relations are proved to be different among regions, regional specific equations need to be developed based on empirical fecal NIRS data record. Embedding the equations into Geographic Information System (GIS) fed with time series of GDD, a real time and forecasting cattle diet quality map could be produced. The map could be of great use in regional or national management of cattle industry.

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