UNDERSTANDING THE RELATIONSHIP BETWEEN WEATHER VARIABLES, DRY MATTER INTAKE, AND AVERAGE DAILY GAIN OF BEEF CATTLE

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ABSTRACT

The current National Academies of Sciences, Engineering and Medicine dry matter intake (DMI) prediction models are inadequate for beef cattle in the Northern Great Plains. Four studies were conducted to account for variation in DMI and average daily gain (ADG) caused by weather variables. Experiment 1 and 2 had 13,895 steer-weeks observations, experiment 3 had 13,739 steer-weeks observations, and experiment 4 had 2,161 cow-weeks observations, respectively. Experiment 1 examined how ambient temperature and solar radiation influence DMI of beef steers. In experiment 2, 3, and 4, we examined how ambient temperature, range of temperature, dew point, solar radiation, wind speed and their lags (two-week lag and monthly lag) influenced DMI of beef steers, ADG of beef steers, and DMI of beef cows, respectively. After adjusting for week of the year, linear and quadratic relationships of predictor variables on response variables were evaluated. In experiment 1 and 2, body weight (BW) had linear and quadratic relationships with DMI of steers. In experiment 3 and 4, BW had linear relationships with ADG of steers and DMI of cows, respectively. Week of the year, BW, and dietary energy density were in the base model in experiment 1, 2 and 4 while in experiment 3, DMI was also accounted for. For the models, stepwise regression procedures were utilized. In experiment 1, ambient temperature and solar radiation interacted ($P = 0.0001$) and accounted for additional variation in DMI of beef steers. In experiment 2, weather variables and their interactions ($P = 0.0001$) accounted for additional variation in DMI of beef steers. In experiment 3, weather variables ($P = 0.0001$) accounted for additional variation in ADG of beef steers. In experiment 4, wind speed interacted ($P < 0.001$) with ambient temperature and range of temperature and accounted for additional variation in DMI of beef cows. These studies show that weather variables interact and cause variation in DMI and ADG in beef cattle. This has helped in better

understanding the relationship between weather variables with DMI and ADG, improve the accuracy of DMI and ADG prediction, and will help beef cattle producers manage their feed resources more efficiently.

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DEDICATION

This dissertation is dedicated to God, the master of the universe, the beneficent and the most merciful. Then, to my Late Mum, Kudirat I. Yusuf, I know you are happy and proud of me where you are now.

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LIST OF ABBREVIATIONS

ADF..Acid detergent fiber

ADG..Average daily gain

BCS...Body condition score

BI...Base intake, kg DM/day

BUT...Butyric acid, g/kg DM

BW...Body weight

C...Concentrates, kg DM/day

C%...Concentrates, % of diet

CF..Crude fiber, % of DM

Cg_{MW}...Concentrates, $g/W^{0.75}$/day

Cgw...Concentrate, g/W/day

cNE..Concentrate NE_l content, MJ/kg DM

CW...Post-calving weight, kg

DE_{MJ}...Digestible energy, MJ/kg DM

DM...Dry matter

DMD..Dry matter digestibility, %

DMI...Dry matter intake, kg/day

DMIf..Dry matter intake (kg/day) when fill is limiting intake

DMIm..Dry matter intake (kg/day) when metabolic factors are limiting intake

Em + p...Chemical energy in milk and retained protein, MJ/day

F...Fecal DM, kg/454 kg live weight

F%...Fat content in milk, %

FCM ....Fat corrected milk, kg 4% milk/day

FS ....Frame size

FY ....Milk fat yield, kg/day

Gw...Gestation week

ln ....Logarithm to base 2.71828

iW...Initial live weight, kg

LEG..Content of legumes, % of DM

Log ....Logarithm to base 10

m/s..Meters per second

ME...Metabolizable energy, Mcal/kg DM

MW ....Metabolic body weight, $W^{0.75}$

NDF..Neutral detergent fiber, % of DM

NEm ....Net energy for maintenance. Mcal/kg DM

NH_3N...Ammonia nitrogen, g/kg N

°C...Degrees Celsius

OM ....Organic matter, % of DM

OMDr..Organic matter digestibility of roughage. %

PY ....Protein yield, kg/day

q...Metabolizability value

rNE..Roughage NEi content, MJ/kg DM

SDM%...Silage DM concentration. %

SI ....Silage intake, $g/kg^{0.75}$

SLd..Stage of lactation, day

SLm...Stage of lactation, months

SLw ....Stage of lactation, weeks

W..Live body weight, kg

W/m^2..Watts per square meter

Wc..Live body weight change, kg/day

Wg..Body weight gain, kg/day

Y..Milk yield, kg/day

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CHAPTER 1. LITERATURE REVIEW

1.1. Introduction

Animal models facilitates gathering of knowledge of nutrition, metabolism and physiology that have been acquired through various research studies. The acquired knowledge can be used to increase our quantitative knowledge of animals, sources of variations, and then ultimately help in strategies that will improve animal production.

Our objective as nutritionists, physiologists and biochemists involved in animal research is to increase our current understanding of animals. To achieve this, we must understand environmental factors that affects the animals apart from nutrition, genetics, and management. Over the years, scientists have worked on many aspects of nutrition and management, which have resulted in advancements related to efficiency and general productivity of animals. With the invention of automated feeding systems that can accurately record the number of times an animal visits the feed bunk, the time spent eating, and the quantity of feed consumed, there is boundless amount of data that can be collected from feeding trials over the years which could facilitate the understanding of complex animal-environmental interactions. This has also been made easier by computers that can simulate models, which can facilitate the understanding of important concepts related to feed intake.

It is common to achieve large datasets today related to ruminant’s digestive, metabolic and physiological processes, therefore it is important to understand the relationships that might exist between the animal’s environment and how the environment affects it. This could be possible through improved mathematical models that could be constructed to understand these processes. In the past, research has focused on understanding how temperature affects some digestive, metabolic and physiological processes in ruminants (NRC, 1981), but weather is composed of several other variables such as windspeed, dew point and solar radiation. All these weather variables can have direct or indirect effects on animals.

Research in the past has focused (NRC, 1981; NRC, 1996; NRC, 2000) more on looking at the effect of absolute temperature on animals, but previous temperature could have a long-term effect on many physiological processes since the animal always tries to maintain homeostasis and this process does not happen instantly, even if it does, it effects is usually long lasting.

Reduced productivity in animals is either because of the human factors (management), climatic factors or genetics. Climatic factors play a large role, and this is more serious in areas where there is extreme weather condition. The Northern Great Plains of the United States is an example of extreme weather as temperature falls as low as -30°C during some winters. Another example is in some tropical parts of the world where temperatures as high as 47°C are experienced. These extreme weather conditions affect animals since they will need to either increase heat production to combat the low temperature or look for methods to dissipate the extreme heat through reducing feed intake or other mechanisms. Changes in feed intake from what the producer expects can have adverse impacts on the animal's productivity, thereby reducing the profit of the producer. The thermal environmental factors that could affect animal productivity include ambient temperature, range of temperature, wind speed, dew point and solar radiation. Some of these weather variables may act directly on the animal or interact together with other variables to create a complex weather variable interaction that might be difficult to pinpoint how much each weather variable affects the animal. Cold temperatures are known to increase oxidation rate of feed or energy available in the animal's body to produce enough heat for the animal (NASEM, 2016). Thermal environment also affects the ability of the animal to digest feed. In warmer temperatures, animals are known to digest roughages faster than in colder temperatures (Bhattacharya and Hussain, 1974; Sharma and Kehar, 1961). Heat is required for a lot of biological processes and some enzymes are either activated or at efficiency as temperature increases to a certain point.

Some models (NRC, 1996, 2000; NASEM, 2016) have been created to account for limited weather variables that influence animals, however, many of these models cannot be replicated or used in the Northern Great Plains because of extreme weather conditions experienced in this region. The NRC models also did not utilize dewpoint, but rather relative humidity. The use of relative humidity is flawed because it is dependent on temperature (National Weather Service, 2021). Dewpoint, on the other hand, is not affected by temperature, thereby making it a better measure of air moisture and avoiding having confounded variables in the model.

1.2. Data Mining

Large datasets are changing the world and the way problems are approached, thereby creating reliable solutions that results in making informed decisions that will increase the overall efficiencies of production overall, if properly utilized. As large data sets are collected, there is a need for tools that can investigate the data and discover patterns that are not expected, which can be used to give reports back to the producers for improved livestock production. All this can be done by a process called data mining (Tan et al., 2005). Data mining is simply looking for trends, patterns, and relationships from data that has been collected to produce new information. When examining large data sets, it is important to remember Bonferroni's principle, which states that, if you look hard enough for interesting patterns, you will see them, so keep looking (Shaffer, 1995). When data is being mined, there are four principal tasks: 1. Discovering interesting relationships among variables, 2. Division of the data sets into discrete groups, 3. Assignment of observations to groups, and 4. Prediction of real-valued outputs based on attributes of observational units (Cole et al., 2012).

1.2.1. Data in Animal Research and Production

Data has been used in almost every organization to enhance and generate more accurate descriptions of systems and aspects to make informed decisions (White et al., 2018). With advancement in technology, inexpensive super computers with fast processing speeds, large storage, and connected sensors that monitors individual animals, and their environment has made it easy to collect large amount of nutritional, behavioral, and meteorological data. Statistics are usually used to analyze data that has been collected to understand trends, patterns or relationships that may exist which then leads to better understanding and ultimately new knowledge of that aspect.

With the right analytical framework, data from individual animals like body weights and carcass characteristics or data from cohorts like group weights, or feed ingredients could provide useful information for the herd when analyzed correctly (Theurer et al., 2015). The data analyst must be careful to make sure the data is accurate for meaningful information to be derived from the data. This can only be possible when the data analysis process is well understood by the analyst (Theurer et al., 2015). When feedlot operational data are collected, knowledge of the key principles need to be applied, failure to do so could result in making wrong conclusions and corresponding management changes might not have the targeted effect of the outcome of interest (Lawlor et al., 2004)

1.2.2. Data Cleaning

Data cleaning can simply be defined as detecting and removing errors to make the quality of the data better. There is a myriad of factors that could lead to data quality problems, these include spelling mistakes, missing information, technical problems during data collection or some other uncontrollable factors. Some data must be removed during the data cleaning process otherwise they will affect the overall results of the analysis. The ability to know the type of data that could be deleted from the database depends on the knowledge and experience of the data analysts regarding that subject matter. For instance, in animal science studies, it is impossible for an animal to weigh 2,500 kg or consume 200 kg of feed in a day. Seeing such types of data that is practically impossible signals error in the collected data and calls for the data to be thrown out. A general rule of thumb that can be applied to data is, always remember that the biology of a study should be first and not the statistical analysis, in a nutshell, do not let the statistics or the data drive the biology. There are a few phases to data cleaning procedure as reported by Rahm and Do (2001). After manual inspection, a detailed data analysis might be necessary to detect the kind of errors or inconsistencies that needs to be removed from the data. The next phase is transformation of workflow or mapping, and this depends on the source of the data or how heterogenous the data is. A type of schema translation can be used for some early cleaning to detect single source problems or at later step cleaning to deal with problems from multiple sources such as duplicates. Verification should then be done to test the correctness of the workflow. Transformation can then be executed by either running the extraction-transformation-loading workflow or answering queries from multiple sources of the data. The last stage is the backflow of the cleaned data, after all the errors are removed, the cleaned data should replace the old “unclean” data.

Another easy way to clean data before analysis could be the utilization of some exploratory data analysis which could provide insight into the extent of missing data in the unclean dataset. Simple exploratory analysis utilizing basic summary statistics, boxplots, Q-Q plots, histograms, and scatter plots could help to guide the statistician to know if the data can be used to answer the target hypothesis and in turn will help to guide the best model selection procedure (White et al., 2018).

1.2.3. Multicollinearity

In data modeling, there are some common issues that could be encountered, for this dissertation, multicollinearity will be examined since it is relevant as weather variables have some relationships with each other. Multicollinearity is simply a high degree of linear relationship between the explanatory variables to be modelled. This is more common in multiple linear regression models and could lead to incorrect results of regression analysis. There are some tools used to diagnose multicollinearity, these include variance inflation factor (VIF), condition index and condition number, and variance decomposition proportion (VDP).

When there is a perfect linear relationship between two predictors or explanatory variables X1 and X2, then exact collinearity is said to exist between them. Multicollinearity exists when such type of linear relationship exists between more than two explanatory variables (Kim, 2019). Coefficient of determination (R^2) can be used to measure the level of collinearity or multicollinearity between variables. $R^2 = 0$ represents absence of multicollinearity between the variables while $R^2 = 1$ shows that there is exact multicollinearity between them.

Multicollinearity makes data analyses challenging, and could have an impact on development of models, estimation, and final interpretation, especially when the predictor variables have a strong relationship between them. This also makes it difficult for the researcher to be able to parse out the contribution of each of the predictor variables towards explaining the dependent variable. In regression design, the assumption is that predictors have no collinearity between them (Stevens, 2007). Collinearity also affects the stability of the coefficients across samples to be less representative of the population-level estimate. This lack of stability is because as collinearity increases, the standard error of the regression coefficients also increases. So, it does not only affect the evaluation of predictor contribution but also results in unreliable regression coefficients (O'Brien, 2007). Careful analysis of a correlation matrix of the predictors used in the model may be used to assess the degree of multicollinearity. Another efficient way is using the VIF as stated earlier.

Leamer (1973) reported that when there is multicollinearity in a statistical model, it could result in low R^2, low significance and unreliable estimates. This causes a great concern because data cannot be interpreted using the classic parameter-by-parameter approach, and peculiarities in the maximum likelihood surface makes least square estimates irrelevant (Leamer, 1973). Bias in the variance-covariance matrix and estimates of standard error could occur in multilevel modeling even when the fixed effect could be insensitive to severe multicollinearity (Bonate, 1999; Shieh and Fouladi, 2003).

1.2.4. Variance Inflation Factor (VIF)

As the name implies, VIF shows how much of the dependent variable's variance is inflated. In simple terms, VIF is directly related to the regression coefficient that is associated with a predictor variable and it provides an efficient assessment of the collinearity effect of the regression coefficient's estimated variance (O'Brien, 2007). Most statistical software can produce VIF statistics and researchers often use them. Even so, there is no clear guidance about which values of VIF are too large and how the researcher should respond to it (O'Brien, 2007).

Some recommendations were provided by O'Brien, (2007) on how to manage the issues of multicollinearity in data. One suggestion was to combine predictor variables that are conceptually similar and share high correlation to a single measure and then use the newly created single measure in the regression model. The other suggestion is to remove the collinear variables from the model.

Some general guidelines have been suggested in the literature for assessment when VIF values indicate some concern. When the VIF value is greater than 10, then the predictor variables are highly correlated which indicates a high level of multicollinearity between them (Bowerman and O'Connell, 1990). If the average of the VIF is substantially greater than 1, then there may be a bias in the regression coefficient and the overall model (Bowerman and O'Connell 1990). A study conducted by Blaze and Ye (2012) measured the effect of multicollinearity on the parameter estimates and standard errors in multilevel models by designing a Monte Carlo simulation study. They included a two-level predictor model with correlation between level-1 and level-2 predictors and group-mean centering level-1 predictors. In their study, they varied the intraclass correlation coefficients, number of groups and cases per group. The result of their simulation findings was consistent with other simulation studies that examined the effects of multicollinearity in regression analysis. High levels of multicollinearity inflated the standard errors and the estimate of the intercept for the random slope component and was biased when multicollinearity existed between level-1 predictors. The fixed effects remained relatively stable even at high levels of multicollinearity. There was an increase in positive bias of standard error estimates with increases in inter-class correlation coefficients. The easiest way to solve the issue of multicollinearity is by removing one or more of the related variables from the model, which will likely improve the model fit by changing the Akaike information criterion (AIC) and

Bayesian information criterion (BIC) to lower values without losing model information (Kaps and Lamberson, 2017).

1.3. Dry Matter Intake

For any successful nutrition program or production, understanding and predicting dry matter intake (DMI) is important. DMI is dependent upon the interaction of the animal, diet, and the feeding environment (Mertens, 1987). The extent in which diets meet the nutrient requirement of beef cattle for their maintenance and growth is dependent on the accurate estimate of feed intake. However, this is challenging because of the number of factors that affect feed intake in cattle (Forbes, 2003). What makes it more challenging is that control over the nutrient supply is largely determined by the end products from ruminal fermentation of their rumen microbiome. For this reason, nutrient requirement of the ruminant animal can be achieved by selection of diet and regulation of intake from nutritionally formulated diets that meets the required animals' nutrient requirement (Ellis et al., 1999). Numerous studies have been conducted to better understand DMI (Weston, 1966, 1985, 1989; NRC, 1984, 1987, 1996, 2000; Mertens, 1987, Forbes, 2007, Ginane et al., 2015).

1.3.1. Mechanism of DMI Control

Several mechanisms of DMI control have been explained. Some authors attribute it to physical or physiological factors while others attribute it to metabolic control. However, there has been disparities in the described mechanisms of intake control by these authors (Tolkamp and Katelaars, 1992, Forbes, 2003; Allen et al., 2009). Considering the complication in understanding the mechanisms of control of DMI, some authors have suggested using empirical models. Fisher (2002) suggested that empirical models will be of considerable value towards understanding DMI. Some authors have attributed DMI to NEm intake (NRC, 1984), metabolizable energy (ARC, 1980) and body weight, while some authors have adjusted BW using the relative BW of the animal (CSIRO, 2007). Using dietary energy in the models suggested by the above authors (NRC, 1984; ARC;1980, and CSIRO, 2007) is useful because it partially accounts for the influence of gut fill, energy demand, and nutrients effect which are all components that have been addressed by previous authors in their DMI control theories (NASEM, 2016). An interaction of complex biological systems is reflected by the complexity of DMI. The known theory of DMI is explained by Tedeshi and Fox (2016). Tedeshi and Fox (2016) explained two known general theories of DMI control, the physical and metabolic theories. The physical theory explains that mechanoreceptors in the rumen signals ruminal distention, which limits intake of bulky materials. While on the other hand, the metabolic control of DMI regulators have three effects: chemostatic, thermostatic and lipostatic (Fisher et al., 1987; Forbes, 1980). To explain further, chemostatic control is the major mechanism related to the energy concentration of the diet and the amount of VFA in the rumen, blood or liver (Forbes, 1980), concentration of fatty acids in the small intestine and balance of amino acids in ruminant tissues (Ellis et al, 1999). The impact of cold or heat stress is attributed to the thermostatic effects, whereas the body fat of the animal is attributed to lipostatic function (Fisher et al., 1987). To summarize, although it has been well established that DMI is determined by both physical and metabolic regulators, BW remains the biggest regulator of DMI for all domestic ruminant species (Tedeshi and Fox, 2016).

1.3.2. Factors Affecting DMI of Cattle

There are several factors that affect DMI of cattle, all these factors can be grouped under four major areas: physiological, environmental, dietary and management.

1.3.2.1. Physiological Factors

The degree of fatness of cattle has been explained to affect feed intake (NRC, 1987). As an animal gets fatter there are receptors that generate feedback signals (e.g. leptin or unsaturated fatty acids in circulation) which then affect centrally controlled DMI regulation (NRC, 1987). Sex of the animal has been reported to have some effects on DMI, although its effect is thought to be limited (NASEM, 2016). More recently it has been observed that sex does not have a significant effect on DMI using large database of DMI data including average BW and dietary NEm (Anele et al., 2014). Age at which an animal was placed on feed for finishing affects DMI. When younger animals are placed for finishing, they have been reported to consume lesser DMI per unit BW compared to older animals (e.g., calves vs. yearlings) (NASEM, 2016). This difference has been linked to the effect of compensatory feed intake and growth by the older animal (NRC, 1987). Hicks et al. (1990) reported an increase in DMI by yearlings compared to calves and reported a difference in DMI over time.

The physiological state of cattle also affects DMI. ARC (1980) reported 35 to 50% increases in DMI for lactating animals vs. non-lactating animals. In a study by Minson (1990), they noted an increase in DMI of 30% with lactation. Greater intake by beef cows that have been bred for greater milk production would also be expected. This is supported by the reports from ARC (1980) and NRC (1987), where they suggested that DMI increase by 0.2 kg/kg fat corrected milk. As pregnancy advances, DMI has been reported to decrease, most especially in the last month (ARC, 1980, NRC, 1987). NRC (1987) reported a decrease of 2% per week during the last month of pregnancy. There is a wide variation in the frame size of beef cattle. Crosses from Holstein × Beef crosses has been reported to consume more DMI relative to BW compared to beef breeds (NRC, 1987).

1.3.2.2. Environmental Factors

There have been extensive reports in the literature on how environmental factors affect DMI. Many studies and reviews have been done on the influence of thermal environment, especially ambient temperature on DMI (Young, 1987, 1981; NRC, 1987; Young et al., 1989; Delfino and Mathison, 1991). Ambient temperature has an influence on DMI of beef cattle because cattle adjust their maintenance energy requirement to cope with effective ambient temperature outside their thermoneutral zone (Young, 1987; Young et al., 1989). In experimental situations, DMI has been reported to increase in cold temperatures below the thermoneutral zone and on the other hand, DMI decreases when the ambient temperature becomes elevated above the thermoneutral zone. (NRC, 1987). Kennedy et al. (1986) noted that a digestive tract response might be responsible for greater DMI when they observed an increase in ruminal motility and digesta passage as animals become cold stressed. Thermal susceptibility, acclimation and diet have been reported to vary from animal to animal as they respond to change in temperature (Young, 1987). A study by Stanton (1995) did not find any increase in DMI in cattle confined in outdoor lots and fed finishing diets during cold stress. NASEM (2016) noted that other adverse environmental conditions like wind, precipitation, mud and so on could accentuate the effects of temperature. There is a lesser understanding on the effect of season or day length on DMI compared to ambient temperature. Hicks et al. (1990) grouped their intake data into four seasons so they could account for seasonal variation. However, it is difficult to parse out photoperiod since, temperature, animal, and management practice could influence DMI at any given time. Ingvartsen et al. (1992), reported an increase of 0.32%/h increase in daylength when they evaluated the effect of daylength on DMI using Danish black and white bulls. NASEM (2016) noted that there would be an expected increase in DMI of 1.5-2% in long-day months (summer season; July in the Northern Hemisphere) and 1.5 to 2% decrease in short-day months (winter season; January in the Northern Hemisphere).

1.3.2.3. Dietary Factors Affecting DMI

Feed availability affects the amount of DMI consumed. A summary by Rayburn (1986) utilizing the reviewed data by NRC (1987), reported that grazing cattle consumed more forage when there was more forage in the pasture compared to when forage was lesser. Bite size is decreased as forage mass goes below 2000 kg DM/ha, and grazing time only partially compensates for this decrease (Minson,1990). Forage type and sward structure also influence the change in DMI. Stage of growth also affects DMI, cattle and sheep have been reported to feed on actively growing (green) pasture as compared to senescent ones, for this reason the effect of total forage availability on DMI might be affected by forage composition (Bird et al., 1989; Minson, 1990).

It has been reported that growth promoting implants increase feed intake. A study by Rumset et al. (1992), observed that, DMI increased in implanted cattle from 4 to16% depending on the type of implant. For nonimplanted cattle, Fox et al. (1988) suggested that predicted intake should be reduced by 8%. However, it was cautioned by NASEM (2016) that care should be taken when adjusting DMI arbitrarily since all the models used in the NRC (1996, 2000) models were from cattle that were implanted. DMI is reduced by including an ionophore (Monensin) in the diet, this is more observed in diets with high forage or silage. Studies by Galyean et al. (1992) noted a decrease in DMI by 4% when monensin (31 mg/kg diet) was included.

Amount of nitrogen in the diet also affects DMI, Galyean and Goestch, (1993) noted that when nitrogen is deficient in the diet, especially when high fiber forages are fed, it results in deficiency in ruminal nitrogen resulting in decreased fiber digestion, and when supplemental nitrogen is provided, DMI often increases. NRC (1987) supported this by noting that reposes in forage intake because of added nitrogen is more typical when the crude protein content of the diet is lower than 6 to 8%. Processing of feed also affects DMI, although it depends on the type of feed. When forages are ground, DMI increases and this could be because of the increased passage rate, and when concentrates are too finely ground, it reduces DMI (Galyean and Goestch, 1993).

1.3.3. Previous Research on DMI Prediction Model

Understanding the complex interaction between feed intake, and how it is regulated dates to as far back as 1964. Significant research and reviews have been conducted to understand how several factors (Animal, feed, environment, and management) interact to influence intake regulation and prediction (Conrad et al., 1964; Journet et al, 1965; Baile and Forbes, 1974; Weston, 1982; Grovum, 1987; NRC, 1987).

Table 1.1. Models for prediction of voluntary intake of growing cattle

Reference	Model for prediction of total dry matter intake (kg/day)
Simple and multiple regressions:	
MAFF (1975)	DMI = (31.4 – 0.03 W) W/1000
ARC (1980)	DMI = Coarse diets DMI = (24.1 + 106.5 q + 37 C% / 100) MW /1000 Fine diets: DMI = (116.8 – 46.6q) MW/1000
NRC (1984)	DMI = [(0.1493 NEm – 0.046 $(NEm)^2$ – 0.0196) MW] [1 + 0.05 FS] where: FS = -2 for medium-frame heifers; FS=0 for medium frame steer calves, large-frame steer calves and medium-frame yearling steers.
Schwarz et al. (1988) Rook and Gill (1990)	DMI = 3.72 In (W) + 0.054 SDM% + 0.128 C – 16.98, (for maize silage only) DMI = [(0.0155iW -0.5816 C_{gMW} + 0.894 SDM% + 12.98 pH – 0.442 BUT + 0.445 N + 0.0257 OMD – 25.5) + C_{gMW}] MW/1000 (Equation 1.1)
Rook et al. (1990)	DMI = [(-0.4591C_{gMW} + 0.754 SDM % - 0.232 BUT + 0.367 N + 0.0184 OMD + 38.68) + C_{gMW}] MW/100 (Equation 229; ridge regression) DMI = [(-0.4590 C_{gMW} + 0.988 SDM% - 0.2563 BUT + 53.77) + C_{gMW}] MW/1000 (Equation 2.18; reduced ordinary least square model)
More complex systems	
Lewis (1981)	DMI = (SDMI + C_{gW}) W/1000, where SDMI = 0.921 SI – 0.0271 C_{gW} SI – 0.0247 $(C_{gW})^2$ + 1, where: SI = 1.00 SDM% + 0.161 OMD – 0.02 NH_3N – 0.0154 W + 45 (SDMI is silage intake when CgW amounts of concentrates are fed and SI is silage intake when silage is fed solely).
Fox and Black (1984)	DMI = BI + BI (CAT + FA + T + Mud), where: BI = 0.1 MW - 0.002 MW (W* - 364)/22 – 0.002 MW (NEm – 1.27)/ 0.02, * for W> 364 CAT: Correction for category of animals: CAT = 0.10 for yearlings; CAT = 0.17 for Holsteins; Cat = 0.09 for Holsteins × British FA: Correction for feed additives: FA = -0.10 for monensin; FA = -0.02 for lasalocid. T: Correction for temperature: T = -0.35 > 35˚C (no night cooling) T = -0.10 > 35˚C (night cooling) or 25 -35 ˚C T = 0 15 to 25˚C T = 0 5 to 15˚C T = 0.03 -5 to 5 ˚C T = 0.05 -5 to -15˚C T = 0.07 <-15˚C T = 0.16 Mud: Correction for mud: Mud = -0.15 for mild mud (10-20cm); Mud = -0.30 for severe mud (30-60 cm)
Cornell-system (NRC, 1987; Fox et al., 1988; Rayburn and Fox, 1990)	DMI = BI + BI (CAT + Sex + EBF + AS + FA + Diet + Leg + T + Mud), where: BI = (0.1493 NEm – 0.046 $(NEm)^2$ – 0.0196) MW CAT: See Fox and Black (1984) Sex Correction for sex: ♂ sex = 0 ♀sex = 0.03 EBF: Correction for empty body fat content, % at equivalent weight (See NRC, 1987): ≤ 21.3% EBF = 0; 23.8%: EBF = -0.03; 26.5%: EBF=-0.10; 29.0%: EBF=-0.18 ; 31.5%:EBF = -0.27 AS: Correction for nonuse of anabolic stimulant AS =-0.08 FA: Correction for feed additives: Monensisn 33g/1000kg feed: FA = -0.10 Monensin 22g/1000kg feed: FA = -0.06 Lasalocid: FA = -0.02 Diet: correction for finely processed diets: For NEm = 1.00: Diet = 0.47 NEm = 1.35: Diet = 0.20 NEm = 1.70: Diet = 0 NEm = 2.05: Diet = -0.17 Leg: Correction for legume content: Leg = (1.1088 – 0.3889 ME) (LEG/100-0.5) T: See Fox and Black (1984). Mud: See Fox and Black (1984)

Adapted from Ingvartsen, 1994.

Table 1.2. Different models for prediction of voluntary intake in dairy cows

Reference	Model for prediction of total dry matter intake (kg/day)
	Multiple regressions:
Journet et al. (1965)	DMI = 0.0074 W + 0.27 Y + 6.70
Johnson et al. (1966)	DMI = 1.46 SLw + 0.08 Y + 0.09 Wc + 1.08 BCS + 6.71, for SLw ≤ 15 DMI = 0.05 Y + 0.09Wc - 5.0 BCS - 0.12 Gw + 14.57, for SLw >15
Curran et al. (1970)	DMI = (0.332 Wc + 0.730 C + 0.644 OMDr - 0.33 Y + 0.005 Y^2 - 7.68) / (OM/100), for 1 ≤ SLw ≤4 (model no 19). DMI = (0.862 C - 1.104 DMD_r + 0.0145 $(DMD_r)^2$ + 39.51)/(OM/100), for 5 ≤ SLw≤ 8 (model no 24) DMI = (1.544 C + 0.183 DMD_r + 0.370 Y - 0.022 CY- 8.53) / (OM/100), for 9≤ SLw ≤ 12 (model no 29) DMI= (0.658 C + 0.184 DMD_r + 0.094 Y – 3.28) / (OM/100), for 13≤SLw≤16 (model no. 35)
McCullough (1973)	DMI = 0.008 W + 4.7 Wc + 0.36 Y - 0.028%
MAFF (1975)	DMI = 0.025W + 0.1 Y
Bines et al. (1977)	DMI = 0.0113 W + 0.16 Y + 2.45 Wc +4.25
Brown et al. (1977)	DMI = exp (0.5198 + season + 0.000675W - 0.000827 SLd + 0.14807 ln(SLd) + 0.33922 In (Y) + 0.09927 FY + 0.01800 CF - 0.000557 CF^2) Season: fall-winter=0.0418; spring = -0.0224; summer = - 0.0188
Vadivelo and Holmes (1979)	DMI = 0.013 W + 0.404 C - 0.129 SLw + 4.120 log(SLw) + 0.140 Y + 0.076
Ostergaard (1979)	DMI = 0.0072 (W - 477) + C - 0.020 C^2+ 6.93, for SLw ≤ 24 in primiparous cows DMI = 0.0072 (W - 538) + C - 0.020 C^2 + 7.87, for SLw < 24 in multiparous cows
ARC (1980)	DMI = [(0.135MW + 0.2 (Y - 21.4 $SLw^{0.2}e^{-0.04sLw}$)] SLm, where SLm = 0.81 for month l; 0.98 for 2; 1.07 for 3; 1.08 for 4; 1.09 for 5; 1.08 for 6; 1.01 for 7; 0.99 for 8; 0.97 for 9; 0.93 for 10.
McCullough (1981)	DMI = 0.0216W + 0.511 FCM - 0.00529 FCM^2 - 2.51
Yungblut et al. (1981)	DMI = 0.0096 W + 0.34 L + 0.336 Y + 0.528 F% - 0.106 ADF + 3.37
Doyle, 1983	DMI = 0.013W - 0.495C - 0.012C^2 + 0.1187 SLw + 7.721 log (SLw) - 3.417 + C
Neal et al. (1984)	DMI = 0.022W + 0.2Y
Rook et al. (1984)	DMI = 0.00659W – 0.387C +1.486 (FY + PY) + 0.0136 OMD_r – 3.74 + C (multiparous cows only; model 4) DMI = 0.00595 CW + 0.0109 (CW-W) - 0.000066 $(CW\text{-}W)^2$ -0.468 C + 3.309 (FY + PY) + 0.00996 OMD_r + 0.5326 SLw - 0.01923 SLw^2 - 4.63 + C (multiparous cows only; model 6)
Rayburn and Fox (1993)	DMI = 0.0117 W + 0.0749 SLd + 0.281 FCM, for SLd <84 DMI = 0.023 W + 0.0201 SLd + 0.286 FCM - 0.0979 NDF, for SLd > 70
	More complex systems
Conrad et al. (1964)	DMI = 3.578 $(2.2W)^{0.513}$ $DMD^{0.461}$ $(0.24E_{m+p})^{0.251}$ for DMD ≥ 67% DMI = $10^{-5.639}$ $(2.2\ W)^{0.99}$ $DMD^{1.53}$ $(2.2\ F)^{1.01}$, for DMD < 67%
Forbes (1977)	DMIm = 3.55 $(2.2W)^{0.51}$ + $DMD^{-0.46}$ $(0.24\ E_{m+p})^{0.25}$ DMIf = 10 - 5.639 $(2.2\ W)^{0.99}$ $DMD^{1.53}$ $(2.2\ F)^{1.01}$, where F=4.0 [CW/5 – (W-CW)/3] / (CW/5)
Lewis (1981)	DMI = SDMI MW/1000 + 0.00175 Y^2 + C, where SDMI = 1.068 SI - 0.00247 C_{gMW} SI - 0.00337 $(C_{gMW})^2$ - 10.9, where: SI = 1.03 SDM% + 0.516 OMD – 0.05 NH_3N + 45 (SDMI is silage intake when C_{gMW} amounts of concentrates are fed and SI is silage when silage is fed solely).
Mertens (1987)	DMIm = (0.335 MW + 3.10 FCM – 20.60 WI + 21.77 Wg) / (C%/100 cNE+ (100 – C%) / 100 rNE) where: cNE = app. 7.95 MJ /kg DM; rNE=9.72 - 0.0904 NDF % DMIF = 0.011 W / (NDF/100) DMI = DMIm for DMIm <DMIf; else DMI = DMIf
NRC (1987)	for lactating cows: DMI = (1.896 $W^{0.593}$ $FCM^{0.33}$ $e^{0.16\ wc}$) / $DE_{MJ\ if}$ DMI ≤ DMIf = 5.4 W/5 (100-DMD); else DMI = DMIf. For nonlactating pregnant cows: DMI = (1.896 $W^{0.593}$ $e^{0.16\ wc}$)/ $DE_{MJ,}$ If DMI ≤ DMIf = 5.4 W/5 (100 - DMD); else DMI = DMIf.

Adapted from Ingvartsen, 1994.

1.4. Dietary Energy

Energy is simply defined as the ability to do work. It is measured using standard conditions and the System International (S.I.) unit of energy is the Joule. Combustion calorimeters are typically standardized by nutritionists using purified benzoic acid whose energy content has been determined in electrical units and it is computed in terms of joules/g mole (NRC, 1984, 1996, 2000). We cannot talk about energy and not state it in terms of calories which is more used in nutrition in North America than the Joules. The calorie has been standardized to equal 4.184 joules and is approximately equal to the amount of heat required to raise 1g of water from 16.5˚C to 17.5 ˚C, and this is referred to as the 17˚C calorie (NASEM, 2016). Energy supplied to animals is usually expressed as Gross energy (GE), but GE does not represent the amount of energy available to the animal, for this reason GE is not practical in terms of assessing the amount of energy from a particular diet that is available to the animal. Tracing history, the concept of energy expenditure and measurements dates to the classic works by various authors like Armsby and Fries, (1915), Brody (1945), Kleiber (1961), Blaxter (1962), Lofgreen and Garrett (1968) and many others. To improve ruminant production, it is necessary to identify processes that consume energy associated with maintenance and productive functions more efficiently (Caton and Olson, 2006). This is because, ruminants unlike monogastrics use a high proportion of their metabolizable energy to maintain their body (maintenance). In fact, in beef cattle, over 70% of energy expenditure is used for maintenance functions (Ferrell and Jenkins, 1985)

1.5. Maintenance Energy

The energy required by an animal that will result in no loss or gain of energy from the tissues of the animal body is termed maintenance energy. Temperature regulation, metabolic processes, and physical activity are processes that comprise the maintenance energy requirement. Since the metabolizable energy required for maintenance functions in mature beef cows represents approximately 70% of total metabolizable energy (ME) supply. Adequate energy must be provided for maintenance. NASEM (2016) reported that even at very high intake in growing cattle, the amount of energy utilized for maintenance is rarely less than 40% of the total ME. Maintenance energy requirements in animal production has been measured basically using three methods, including, feeding trials, calorimetric methods, and comparative slaughter methods. Maintenance energy expenditure as reported by NASEM (2016) is dependent on factors like BW of the animal, the breed or genotype, sex, age, season, temperature, physiological state, and previous plane of nutrition.

1.6. Weather Variables

1.6.1. Ambient Temperature

The temperature of a dry bulb thermometer is referred to as ambient air temperature. In livestock production, animals are exposed to various components of the climatic environment, and for this reason, NRC (1981), created an index to collectively represent the thermal effect of temperature on an animal. They termed this the effective ambient temperature (EAT). They described the EAT in terms of environmental heat demand. NRC (1981) defined EAT as the temperature of an isothermal environment without appreciable air movement or radiation gain that results in the same heat demand as the environment in question. The NRC (1981) explained that several attempts have been made in quantifying EAT but that has been challenging because of the physiological and metabolic mechanisms adopted by animals to combat thermal stress which in turn influences the environmental heat demand. The NRC (1981) summarized by stating that EAT is a useful concept when predicting the thermal environment of animals and stated that several other weather factors such as thermal radiation, wind, and humidity influence the environmental heat demand in livestock. Ambient temperature also influences thermoneutral zone (TNZ). The TNZ in animal production has been defined as the temperature in which the body temperature of animals remains normal, there is no sweating or panting, and heat production by the animal remains at a minimum (Mount, 1974).

1.6.2. Dew Point

The temperature at which water vapor in the air condenses into liquid water is referred to as the dew point. Accurate and reliable measurement of dew point plays a major role in climatological and agricultural operations (Feld et al., 2013). Most animal studies have used relative humidity to measure the amount of moisture in the air, but relative humidity is dependent on temperature and might not be a good measure of the moisture content of the air. The National Weather Service (2021) stated that relative humidity can be misleading and explained why by using this example. Let us say a temperature of -1°C and a dew point of -1°C will give a relative humidity of 100%, but a temperature of 27°C and a dew point of 15.6°C produces a relative humidity of 50%. It would feel much more "humid" on the 27°C day with 50% relative humidity than on the -1°C day with a 100% relative humidity. This is because of the higher dew point. The National Weather Service (2021) explained that to get a real measure of how dry or humid, the weather outside is, it is better to look at the dew point instead of relative humidity. The higher the dew point, the higher the weather will feel more humid.

1.6.3. Wind Speed

Wind speed is the speed at which the air moves and affects the thermal balance of an animal's body. When wind speed is low to moderate, it has a cooling effect on an animal and helps in lowering their body temperature. In the winter, wind speeds of 5 -7 m/s and temperatures lower than -20˚C can cause frostbite in humans and cause excessive cold stress in animals, which can lead to decreased DMI and efficiency (Ruban et. al., 2020). In the summer on the other hand, high wind speed is beneficial to the animal because significant air movement can assist in the removal of excessive heat from the animals through evapotranspiration. The NRC (1981; 2000) and NASEM (2016) reported that wind speed accentuates the effect of temperature, especially in cold weather.

1.6.4. Solar Radiation

Solar radiation (or solar irradiance) is the amount of electromagnetic radiation emitted by the sun. The SI unit for solar radiation is watt per meter square (W/m^2). Solar radiation reaching the earth drives almost all known physical and biological systems on earth (Qiang, 2003). The typical peak value of solar radiation reaching the terrestrial surface facing the sun on a clear day around solar noon at sea level is 1000 W/m^2. Solar radiation has been reported to reach the earth surface by direct beam, diffuse solar radiation, and of negligible amounts, reflected radiation (Ioan and Calin, 2017). Some factors affect the amount of solar radiation that reaches to the earth surface, these include, the elevation of the earth surface, clouds, and the angle of the sun. Solar radiation has been reported to be a significant factor that reduces the metabolic requirement of cattle by 25- 26% during the day (Keren, 2005). A report by Renecker and Hudson (1986) stated that the positive coefficient between temperature and short-wave solar radiation interaction may reflect warm, sunny days, when cattle were near or above their upper critical temperature. In animals, the amount of solar radiation absorbed by their body depends on sky conditions, ground cover and the shape and orientation of the body relative to the sun. Keren (2005) reported that when cattle orient their body perpendicularly to the sun, that position increase the surface area of the cow’s body exposed to short-wave solar radiation.

1.6.5. Range of Temperature

Range of temperature is the difference between the minimum and maximum values of temperature observed at a location within a day. Temperature changes during the day and at nights and the variation in temperature that happens from hot temperatures experienced during the day to cooler temperatures at night is termed diurnal temperature variation.

1.7. Literature Cited

Allen, M. S., B. J. Bradford, and M. Oba. 2009. Board-invited review: The hepatic oxidation theory of the control of feed intake and its application to ruminants. J Anim. Sci. 87:3317-3334 DOI: 10.2527/jas.2009-1779

Anele, U. Y., E. M. Domby, and M. L. Galyean. 2014. Predicting dry matter intake in growing and finishing beef cattle: Evaluation of current methods and equation development. J. Anim. Sci. 92:2660-2667 DOI: 10.2527/jas.2014-7557

ARC. 1980. The Nutrient Requirements of Ruminant Livestock. Surrey, U.K: Commonwealth Agricultural Bureaux.

Armsby, H. P., and J. A. Fries. 1911. The influence of Type and Age Upon the Utilization of Feed by Cattle. Bulletin No. 128. Washington D. C. U.S Department of Agriculture, Bureau of Animal Industry.

Baile C. A. and J. M. Forbes 1974. Control of feed intake and regulation of energy balance in ruminants. Physiol. Rev. 54:160-214. DOI: 10.1152/physrev.1974.54.1.160

Bhattacharya, A., and M. Uwayjan. 1975. Effect of high ambient temperature and low humidity on nutrient utilization and on some physiological responses in Awasi sheep fed different levels of roughage. J. Anim. Sci. 40:320. DOI: https://doi.org/10.2527/jas1975.402320x

Bines, J. A., Napper, D. J. and, V.W. Johnson. 1977. Long-term effects of level of intake and diet composition on the performance of lactating dairy cows. 2 Voluntary intake and ration digestibility in heifers. Proc. Nutr. Soc., 36: 146A.

Bird, P. R., M. J. Watson, and J. W. D. Cayley. 1989. Effect of stocking rate, season and pasture characteristics on liveweight gain of beef steers grazing perennial pastures. Australian Journal of Agricultural Research 40:1277-1291 DOI: https://doi.org/10.1071/AR9891277

Blaxter, K. L. 1962. The Energy metabolism of Ruminants. Springfield IL,: Charles C Thomas.

Blaze, T. J., and F. Ye. 2012.The Effect of Within- and Cross-Level Multicollinearity on Parameter Estimates and Standard Errors in Multilevel Modeling with Different Centering Methods, American Educational Research Association Conference, Vancouver, British Columbia, Canada

Bonate, P. L. 1999. The Effect of Collinearity on Parameter Estimates in Nonlinear Mixed Effect Models. Pharm. Res. 16:709–717 DOI: https://doi.org/10.1023/A:1018828709196

Bowerman, B. L. and O'Connell, R. T., 1990. Linear Statistical Models: An Applied Approach, Second Edition, Duxbury Press, Belmont, California

Brody, S. 1945. Bioenergetics and Growth. New York: Hafner.

Cole, J. B., S. Newman, F. Foertter, I. Aguilar, and M. Coffey. 2012. Breeding and Genetics Symposium: really big data: processing and analysis of very large data sets. J. Anim. Sci. 90:723-33. DOI: 10.2527/jas.2011-4584.

Conrad, H. R., A. D. Pratt, and J. W Hibbs. 1964. Regulation of feed intake in dairy cows;Change in importance of physical and physiological factors with increasing digestibility. J. Dairy Sci. 47:54-62 DOI: https://doi.org/10.3168/jds.S0022-0302(64)88581-7

CSIRO. 2007. Nutrient Requirements of Domesticated Ruminants. Collingwood, Australia: CSIRO Publishing.

Curran, M. K., Wimble, R. H., and W. Holmes. 1970. Prediction of the voluntary intake of food by dairy cows. 1. Stall-fed cows in late pregnancy and early lactation. Anim. Prod., 12: 195-212. DOI: https://doi.org/10.1017/S0003356100038770

Delfino, J. G and G. W. Mathison. 1991. Effects of cold environment and intake level on the energetic efficiency of feedlot steers. J. Anim. Sci. 69:4577-4587 DOI: 10.2527/1991.69114577x

Doyle, C. J. 1983. Evaluating feeding strategies for dairy cows: a modelling approach. Anim. Prod., 36: 47-57. DOI: https://doi.org/10.1017/S0003356100039921

Ellis, W. C., D. P. Poppi, J. H Matis, H. Lippke, T. M. Hill, and F. M. Rouquette, Jr. 1999. Dietary-digestible-metabolic interactions determining the nutritive potential of ruminant diets. Pages 423-481 in Proceedings of the 5th International Symposium on the Nutrition of Herbivores. H.-J. G. Jung and G.C Fahey Jr., eds. San Antonio TX. American Society of Animal Science.

Feld, S. I., N. C. Cristea, and J. D. Lundquist. 2013. Representing atmospheric moisture content along mountain slopes: examination using distributed sensors in the Sierra Nevada, California Water Resour. Res., 49: 4424-444 DOI: https://doi.org/10.1002/wrcr.20318

Fisher, D. S. 2002. A review of a few key factors regulating voluntary feed intake in ruminants. Crop Sci. 42:1651-1665 DOI: https://doi.org/10.2135/cropsci2002.1651

Fisher, D. S., J. C Burns and K. R. Pond. 1987. Modeling ad libitum dry matter intake by ruminants as regulated by distension and chemostatic feedbacks. J. Theor. Biol. 126:407-418 DOI: https://doi.org/10.1016/S0022-5193(87)80148-0

Forbes, J. M. 1980. Physiological aspects of the regulation of food intake. Ann. Zootech. 29:189-196 DOI: https://doi.org/10.1051/animres:19800512

Forbes, J. M. 2003. The multifactorial nature of food intake control. J. Anim. Sci. 81(suppl):139-144 DOI: https://doi.org/10.2527/2003.8114_suppl_2E139x

Forbes, J. M. 2007. Voluntary Food Intake and Diet Selection in Farm Animals, 2nd edn. CAB International, Wallingford, UK.

Forbes, J. M. 1977. Development of a model of voluntary food intake and energy balance in lactating cows. Anim. Prod., 24: 203-214. DOI: https://doi.org/10.1017/S0003356100011673

Fox, D. G., and J. R. Black. 1984. A system for predicting body composition and performance of growing cattle. J. Anim. Sci., 58:725-739. DOI: https://doi.org/10.2527/jas1984.583725x

Fox, D. G., Sniffen, C. J. and J. D O'Conner. 1988. Adjusting nutrient requirements of beef cattle for animal environmental variations. J Anim. Sci., 66:1475-1495. DOI: https://doi.org/10.2527/jas1988.6661475x

Galyean, M. L., and A. L. Goestch. 1993. Utilization of forage fiber by ruminants. P.p 33-71 in Forage Cell Wall Structure and Digestibility, H. G. Jung, D. R. Buxton, R. D. Hatfield, and J. Ralph, eds. Madison. WI: American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America.

Galyean, M. L., K. J. Malcolm, and G. C. Duff. 1992. Performance of feedlot steers fed diets containing laidomycin propionate concentration on intake pattern and ruminal fermentation in beef steers during adaptation to a high-concentrate diet. J Anim. Sci. 70:2950-2958 DOI: 10.2527/1992.70102950x

Ginane, C., M. Bonnet, R. Baumont, and D. Revell. 2015. Feeding behaviour in ruminants: A consequence of interactions between a reward system and the regulation of metabolic homeostasis. Anim Prod. Sci. 55. 247-260. DOI: https://doi.org/10.1071/AN14481

Grovum, W. L. 1987. A new look at what is controlling food intake. In: Owens, F.N. (ed.) Feed Intake by Beef Cattle. Oklahoma State University, Stillwater, Oklahoma, pp. 1–40.

Hicks, R. B., F. N. Owens, D. R Gill, J.W Oltjen, and R. P. Lake. 1990. Dry matter intake by feedlot beef steers: Influence of Initial weight, time on feed and season of the year received in yard. J. Anim. Sci. 68:254-265 DOI: https://doi.org/10.1093/ansci/68.1.254

Ingvartsen, K. L., H. R. Andersen, and J. Foldager. 1992b. Random variation in voluntary dry matter intake and the effect of day length on feed intake capacity in growing cattle. Acta Agriculturae Scandinavacica A. Animal Science 42:121-126 DOI: https://doi.org/10.1080/09064709209410118

Ioan S., and S. Calin. 2017. In Solar Heating and Cooling Systems, 2017. Retrieved from https://www.sciencedirect.com/topics/engineering/solar-radiation on July, 14th, 2021.

Johnson, W. L., Trimberger, G. W., Wright, M. J., Van Vleck, L.D., and C. R. Henderson, 1966. Voluntary intake of forage by Holstein cows as influenced by lactation, gestation, body weight and frequency of feeding. J. Dairy Sci., 49:856-864. DOI: https://doi.org/10.3168/jds.S0022-0302(66)87959-6

Journet, M., Poutous, M. and S. Calomiti. 1965. Appetit de la vache laitiere. I. Variations individuelles des quantites ingerees. Ann. Zootech., 14:5-37. DOI: https://hal.archives-ouvertes.fr/hal-00886835

Kaps, M., and W. R. Lamberson. 2017. Biostatistics for animal science. 3rd edition Wallingford, Oxfordshire, UK; Boston, MA: CABI.

Katelaars, J. J., M. H., and B. J. Tolkamp. 1992. Toward a new theory of feed intake regulation in ruminants. 1. Causes of differences in voluntary feed intake: Critique of current views. Livestock Prod. Sci. 30:269-296 DOI: 10.1016/0301-6226(92)90039-7

Kennedy, P. M., R. J. Christopherson, and L. P. Milligan. 1986. Digestive responses to cold. Pp. 285-306 in control of Digestion and Metabolism in Ruminants, L.P Milligan, W.L Grovum, and A. Dobson, eds. Englewood Cliffs, NJ:Prentice Hall.

Keren, E. N., and B. E Olson. 2006. Thermal balance of cattle grazing winter range: Model development. J. Therm. Biol. 31:371-377 DOI: 10.2527/2006.8451238x

Keren, I. N. 2005. “Thermal balance model for cattle grazing winter range”. Master’s thesis submitted to the department of Animal and Range Sciences, Montana State University, Bozeman, MT. p. 9

Kleiber, M. 1961. The fire of life: An Introduction to Animal Energetics. New York: John Wiley & sons.

Lawlor D. A., Smith G. D., Kundu D., Bruckdorfer K. R., and S. Ibrahim. 2004. Those confounded vitamins: what can we learn from the differences between observational versus randomised trial evidence? Lancet 363:1724–1727. DOI:10.1016/S0140-6736(04)16260-0

Leamer, E. E., 1973. Multicollinearity: A Bayesian Interpretation. The Review of Economics and Statistics, MIT Press. 55:371-380

Lewis, M., 1981. Equations for predicting silage intake by beef and dairy cattle. In: Harkess, R.D. and Castle, M.E (Eds.), Summary of papers of the VI Silage Conference. The School of Agriculture, Edinburgh. pp. 35-36.

Lofgreen, G. P., and W. N. Garett. 1968. A system for expressing net energy requirements and feed values for growing and finishing beef cattle. J. Anim. Sci. 27:793-806 DOI: https://doi.org/10.2527/jas1968.273793x

MAFF (Ministry of Agriculture, Fisheries and Food). 1975. Energy allowances and feeding systems for ruminants. Tech, Bull. 33, Ministry of Agriculture and Fisheries. Her Majesty's Stationery Office, London, 79 pp.

McCullough, M. E. 1973. Optimum feeding of dairy animals for milk and meat. Univ. Georgia Press, Athens, pp. 127.

McCullough, M. E. 1981. Feed programming of optimum rations for milk production and growth. Dairy Science Miscellaneous Bulletin No. 110. Georgia Cooperative Extension Service.

Mertens, D. R. 1987. Predicting intake and digestibility using mathematical models of ruminal function. Journal of Animal Science, 64, 1548-1558 DOI: https://doi.org/10.2527/jas1987.6451548x

Minson, D. J. 1990. Forage in Ruminant Nutrition. San Diego, CA: Academic Press.

National Academies of Science, Engineering, and Medicine. 2016. Nutrient requirements of beef cattle, 8th Rev. Ed. Washington DC: The National Academies.

National Academies of Science, Engineering, and Medicine. 2016. Nutrient requirements of beef cattle, 8th Rev. Ed. Washington DC: The National Academies.

National Weather Service. 2021. Dew point vs Humidity. Retrieved from https://www.weather.gov/arx/why_dewpoint_vs_humidity on July 14th, 2021.

Neal, H. D. St. C., Thomas, C and J. M. Cobby. 1984. Comparison of equations for predicting voluntary intake by dairy cows. J. Agric Sci., Camb., 103:1-10. DOI: https://doi.org/10.1017/S0021859600043264

NRC. 1981. Effect of Environment on Nutrient requirements of Domestic Animals. National Academy Press, Washington, DC pp 152

NRC. 1984. Nutrient Requirements of Beef cattle, 6th Rev. Ed. Washington, DC: National Academy Press.

NRC. 1987. Predicting feed intake of food-producing animals. National Academy Press, Washington, DC. pp 85.

NRC. 1996. Nutrient Requirements of Beef cattle, 7th Rev. Ed. Washington, DC: National Academy Press.

NRC. 2000. Nutrients Requirement of Beef cattle. Update 2000. 7th Rev. Ed., Washington, D.C: National Academy Press

O'Brien, R. M. 2007. A Caution Regarding Rules of Thumb for Variance Inflation Factors. Qual Quant, 41, 673-690 DOI: 10.1007/s11135-006-9018-6

Ostergaard, V. 1979. Strategies for concentrate feeding to attain optimum feeding level in high yielding dairy cows. Report 482. Nat. Inst. Anita. Sci., Copenhagen, Denmark. Pp 138.

Qiang F. 2003. Radiation (solar). University of Washington, Seattle, WA, USA Pp 1859

Rayburn E. B. 1986. Quantitative Aspects of Pasture Management. Technical Manual. Franklinville, NY:Seneca Trail RC & D.

Rayburn, E. B. and D. G Fox. 1993. Variation in neutral detergent fiber intake of Holstein cows. J. Dairy Sci., 76: 544-554. DOI: https://doi.org/10.3168/jds.S0022-0302(93)77374-9

Renecker, L. A., and R. J. Hudson. 1986. Seasonal energy expenditures and thermoregulatory responses of moose. Canadian J. Zoology 64:322-327 DOI: https://doi.org/10.1139/z86-052

Rook, A. J., and M. Gill. 1990. Prediction of the voluntary intake of grass silage by beef cattle. 1. Linear regression analysis. Anim. Prod., 50: 425--438. DOI: https://doi.org/10.1017/S0003356100004918

Rook, A. J., Dhanoa, M. S. and M. Gill. 1990. Prediction of the voluntary intake of grass silage by beef cattle. 2. Principal component and ridge regression analyses. Anim. Prod., 50: 439-454. DOI: https://doi.org/10.1017/S000335610000492X

Ruban, S., Borshch, O. O., Borshch, O. V., Orischuk, O., Balatskiy, Y., Fedorchenko, M., Kachan, A., and M. Zlochevskiy. 2020. The impact of high temperatures on respiration rate, breathing condition and productivity of dairy cows in different production systems. Anim. Sci. Papers and Reports, 38:61–72 DOI: 20203167447

Rumsey, T. S., A. C. Hammond, and J. P Mc Murtry. 1992. Response to reimplanting beef steers with estradiol benzoate and progesterone: Performance, implant absorption pattern, and thyroxine status. J. Anim. Sci. 70:995-1001 DOI: https://doi.org/10.2527/1992.704995x

Schwarz, F. J., Kirchgessner, M. and R. Carmanns. 1988. Zur Schitzung der Futteraufnahme von Fleckviehbullen bei Mastverfahren mit Maissilage. Ziichtungskunde, 60: 135-142.

Shaffer, J. P. 1995. Multiple hypothesis testing. Annu. Rev. Psychol. 46:561–584. DOI: https://doi.org/10.1146/annurev.ps.46.020195.003021

Sharma, D. S., and N. D. Kehar. 1961. Effect of environmental temperature and humidity on intake and digestion of nutrients. J. Appl. Physiol. 16:611. DOI: https://doi.org/10.1152/jappl.1961.16.4.611

Shieh, Y. Y., and R. T. Fouladi. 2003. The Effect of Multicollinearity on Multilevel Modeling Parameter Estimates and Standard Errors. Educational and Psychological Measurement. 63:951-985. DOI:10.1177/0013164403258402

Stanton, T. L. 1995. Damage control strategies for cattle exposed to cold stress. Pp. 289-298 in Symposium Proceedings: Inatke by Feedlot cattle, P-942, July 1995, F.N Owens, ed. Stillwater:Oklahoma Agricultural Experiment Station.

Stevens, J. P. 2007. Intermediate statistics: A modern approach. 3rd Ed. New York, NY: Routledge.

Tan, P., M. Steinbach, and V. Kumar. 2005. Introduction to Data Mining, Addison-Wesley Longman Publishing Co., Inc, USA.

Tedeshi, L. O., and Fox D. G. 2006. The ruminant nutrition System: An applied model for prediction nutrient requirements and feed utilization in ruminants. Xan Edu, Acton, MA. p. 285

Theurer, M. E., D. G. Renter, and B. J. White. 2015. Using feedlot operational data to make valid conclusions for improving health management. Vet. Clin. North Am. Food Anim. Pract. 31:495–508. DOI:10.1016/j.cvfa.2015.05.004

Vadiveloo, J. and W. Holmes. 1979. The prediction of voluntary feed intake of dairy cows. J. Agr. Sci., 93:553-562. DOI: https://doi.org/10.1017/S0021859600038958

Weston, R. H. 1966. Factors limiting the intake of feed by sheep I. The significance of palatability, the capacity of the alimentary tract to handle digesta and the supply of glucogenic substrate. Australian J. Agr. Res. 17:939-954 DOI: https://doi.org/10.1071/AR9660939

Weston, R. H. 1985. The regulation of feed intake in herbage-fed ruminants. Proc. Nutr. Soc. Aust. 10:55-62.

Weston, R. H. 1989. Factors limiting the intake of feed by sheep. XV. Voluntary feed consumption and digestion in lambs fed chopped roughage diets varying in quality. Aust. J. Agric. Res. 40:643-661. DOI: https://doi.org/10.1071/AR9890643

Weston, R. H. 1982. Animal factors affecting feed intake. In: Hacker, J.B. (Ed.), Nutritional limits to Animal Production from Pastures. Commonwealth Agricultural Bureaux. pp. 183-198.

White B. J., D. E., Amrine, and R.L. Larson. 2018. Big data analytics and precision animal agriculture symposium: data to decisions. J Anim. Sci. 2018 Apr; 96:1531–1539. DOI: 10.1093/jas/skx065

Young B. A. 1987. Food intake of cattle in cold climates. Pp328-340 in Symposium Proceedings; Intake by feedlot cattle, P-942, July 1995, F. N. Owens, ed. Stillwater: Oklahoma Agricultural Experiment Station.

Young B. A. 1981. Cold stress as it affects animal production. J. Anim. Sci. 52:154 DOI: 10.2527/jas1981.521154x

Young, B. A., B. Walker, A.E Dixon, and V.A Walker. 1989. Physiological adaptation to the environment. J. of Anim. Sci. 67:2426-2432 https://doi.org/10.2527/jas1989.6792426x

Yungblut, D. H., Stone, J. B., Macleod, G. K., Grieve, D. G., and E. B. Burnside. 1981. The development of feed intake prediction equations for lactating dairy cows. Can. J. Anim. Sci., 61: 151-157. DOI: https://doi.org/10.4141/cjas81-020

CHAPTER 2. SOLAR RADIATION AS A PREDICTOR VARIABLE FOR DRY MATTER INTAKE IN BEEF STEERS

2.1. Abstract

Solar radiation is an important weather variable that has not been included in previous dry matter intake (DMI) prediction models. Solar radiation affects the overall effective ambient temperature, which in turn contributes to the net gain of heat in an animal's body. This experiment examined the relationship between ambient temperature and solar radiation with DMI in beef steers. Data from 790 beef steers collected between 2011 and 2017 through an Insentec feeding system was used. Daily data was condensed into weekly averages (n = 13,895 steer-weeks). The variables considered for this study were DMI (2.50 to 23.60 kg/d), body weight (197.30 to 796.10 kg), calculated dietary energy density (NEm; 0.793 to 2.970 Mcal/kg), absolute ambient temperature (-23.73 to 21.40°C), two-week lag of ambient temperature (-20.73 to 23.56°C) monthly lag of ambient temperature (-17.95 to 22.74°C), solar radiation (30.81 to 297.12 W/m^2), two-week lag of solar radiation (34.56 to 2714.98 W/m^2) and monthly lag of solar radiation (43.66 to 256.57 W/m^2). Residuals of DMI fitting week of the year (fixed) and experiment (random) were used to generate scatter plots with other explanatory variables to identify if non-linear relationships existed. Body weight and NEm had both linear and quadratic relationships with DMI, while the relationship with DMI for other variables was linear. The MIXED procedure of SAS with Toeplitz variance-covariance structure was used to determine the final model of DMI. After accounting for body weight and NEm in the model, two-week lag of ambient temperature and monthly lag of solar radiation interacted together, accounted for variation in DMI and improved the model fit. Therefore, these two variables and their interactions should be considered in DMI prediction equations of beef steers.

2.2. Introduction

It has been well established that the thermal environment has a great influence on animals (NRC, 1981). Animals compensate for changes in their thermal environment by either adjusting the amount of energy they consume, improving their method of heat dissipation or altering their metabolism. Thornton et al. (2009) reported that when animals do not acclimatize to a sudden change in weather, the result is reduction in production, other extreme losses or even death. The change in the environment due to climate change poses a risk to livestock production, and this necessitates accounting for more of the environmental (weather) variables that influence dry matter intake. This will enable producers to provide for their livestock more accurately with the amount of nutrients and energy to reduce their vulnerability to normal and extreme weather conditions.

Thermoregulation in an animal is dependent on the breed, class, and age and available diet. Thermoregulation is achieved by connecting information from the extrinsic environment with the intrinsic environment, which results in a response for the maintenance of homeostasis. The response could be in the form of lowering metabolism, vasoconstriction, or increasing the quantity of hairs or feathers (Nakamura and Morrison, 2008). Collier et al. (2019) summarized the effect of thermoneutral condition on feed intake in Holstein cows in a controlled environment. They observed a decrease in feed intake as the thermal environment increases from a temperature humidity index (THI) of 57 to 72 (cool to hot). They also reported that an array of environmental factors like ambient temperature, solar radiation, relative humidity and windspeed are known to have either direct or indirect effects on livestock. However, to the best of our knowledge, beef cattle DMI estimation models do not account for the effect that solar radiation may have on DMI. At the same time, the current DMI models available do not fit the northern

Great Plains of North America, where temperatures fall as low as -30°C in the winter (Block et al., 2001). Our objective was to examine how much variation in DMI is accounted for by ambient temperature and solar radiation.

2.3. Materials and Methods

2.3.1. Data Collection

Data used for this experiment were collected from the Beef Cattle Research Complex of North Dakota State University, Fargo, North Dakota located at latitude 46.9027853 degrees North and longitude -96.8418183 degrees West. An Insentec feeding system (RIC feeding system; Hokofarm Group, Marknesse, The Netherlands), which records the amount of feed intake, number of visits, time of visit and meals for each animal, was used for the data collection. The data used were from 10 experiments that were conducted between 2011 to 2017 (Table 2.1).

Table 2.1. Experiments used in this study

Year (week of the year)		n[1] of steers	n of steer-week observations	Breed[2]	Publication
Start	End				
2011 (wk. 45)	2012 (wk. 4)	67	804	AN, SM, and SH	Islas et al., 2014
2012 (wk. 46)	2013 (wk. 5)	94	1120	AN, SM, and SH	Prezotto et al., 2017
2012 (wk. 10)	2012 (wk. 22)	63	819	AN, SM, and SH	Swanson et al., 2014
2013 (wk. 6)	2013 (wk. 22)	66	1098	AN, SM, and SH	Swanson, et al., 2017a
2013 (wk. 38)	2014 (wk. 5)	113	2260	AN-crossbred	Swanson et al., 2018
2014 (wk. 11)	2014 (wk. 22)	44	527	AN, SM, and SH	Swanson et al., 2017a
2014 (wk. 4)	2014 (wk. 22)	81	1339	AN, SM, and SH	Rodenhuis et al., 2017
2015 (wk. 51)	2016 (wk. 18)	61	1211	AN, SM, and SH	Knutson et al., 2020
2016 (wk. 45)	2017 (wk. 20)	134	3432	AN, SM, and SH	Sitorski et al., 2019
2017 (wk. 46)	2018 (wk. 11)	67	1285	AN and SM	Trotta et al., 2019

[1]n=number,
[2]AN = Angus, SM = Simmental, SH = Shorthorn

2.3.2. Weather Data

Data for weather variables were obtained from the North Dakota Agricultural Weather Network (NDAWN) station, which is 2.33 km from the BCRC, for each experiment period included in this study. Each NDAWN station is assumed to adequately represent all weather conditions, except rainfall, in a 32 km radius. For this study, daily summaries of each weather variable were used for each experiment period (NDAWN, 2021).

Weather variables modeled for this study included:

- ambient temperature: the air temperature of the surrounding environment (˚C) and
- solar radiation: sum of all hourly totals of incident solar radiation energy for a 24-hour period from midnight to midnight (W/m^2). Total incident solar radiation flux density is measured in $Watts/m^2$ at approximately 2 m above the soil surface with a pyranometer.
- The two-week lag and monthly lag of each weather variable was also considered. Two-week lag is the average of the previous two week's weather variable while monthly lag is the average of the previous month's weather variable in question.

2.3.3. Non-Weather Variables

The non-weather variables considered for this experiment include weekly average daily gain (ADG), weekly average daily dry matter intake (DMI), weekly average body weight (BW), dietary net energy of maintenance (NEm), experiment, and the week of the year. Week of the year ranged from week 1 to 22 and week 30 to 52. In this study, only 1 experiment had observations for weeks 23 to 29 which will result in inadequate sample and cause scaling issues if they were included in models.

2.3.4. Data Management

The daily feed intake data was averaged into weekly averages to reduce the day-to-day fluctuation. The weekly dry matter analysis of the diet fed from each experiment was matched with the weekly feed intake to calculate the actual DMI consumed by each animal. Weekly BW for each animal was calculated from the monthly BW data values by using simple linear regression. Values for daily ambient temperature and solar radiation were converted into weekly averages. Dietary energy density (NEm,) was calculated by using the equation of Lofgreen and Garrett (1968) and Zinn and Chen (1998) using initial BW, final BW, average daily gain (ADG) and average DMI. Table 2.2 shows the descriptive statistics of the variables used for this study.

Table 2.2. Descriptive statistics of variables

Variable[1]	Mean	Minimum	Maximum	SD[2]	SE[3]
BW, kg	474.18	197.31	796.06	99.04	0.84
DMI, kg/d	10.69	2.50	23.60	2.76	0.02
NEm, Mcal/kg	2.01	0.79	2.97	0.30	0.00
Absolute ambient temperature, ˚C					
No lag	-2.01	-23.73	21.40	10.45	0.09
Two-week lag	-2.19	-20.73	23.56	9.58	0.08
Monthly lag	-2.24	-17.95	22.74	9.05	0.08
Solar radiation, W/m^2					
No lag	112.51	30.81	297.12	64.00	0.54
Two-week lag	107.00	34.56	271.98	58.57	0.50
Monthly lag	104.22	43.66	256.57	54.31	0.46

1 Variable with 13,895 observations,
2SD=Standard deviation.
3SE=Standard error

2.4. Statistical Analysis

Data were analyzed using the MIXED procedures of (SAS Inst., Cary, NC) and within-individual relationship was accounted for using the Toeplitz covariance structure. Week of the year was used as fixed effect and experiment was included as a random effect to output the residuals. Correlation among weather variables was checked using the PROC CORR statement of SAS. Linear and quadratic effects of all the weather variables modeled were tested.

The model for fitting residuals, the base model and the final model were analyzed using the restricted maximum likelihood estimation method (REML), while the maximum likelihood (ML) was used in each step of the forward stepwise addition of variables to the model. Akaike information criterion (AIC) and Bayesian information criterion (BIC) values were used to assess model fit each time a variable was added to the model in a forward stepwise fashion. The parameter estimates were outputted using the solution statement. The full model was refitted using REML to obtain less biased estimates. For all the models, components with ($P < 0.05$), F-values, and their respective AIC and BIC values are reported.

2.5. Results and Discussion

2.5.1. Correlation between BW, NEm and Residuals of DMI

The correlation between BW and NEm, and residuals of DMI using week of the year as a class variable and experiment as a random effect, confirmed that linear and quadratic relationships exist after examining the trend of the scatter plots and testing the linear and quadratic effects of BW and NEm in the model. The correlation coefficients for the relationships for BW and NEm with DMI were 0.2312 ($P < 0.0001$; Figure 2.1.) and -0.073 ($P<0.0001$; Figure 2.2), respectively. For this reason, both the linear and quadratic effect of BW and NEm were included in our model (Table 2.3). Body weight as a predictor for DMI has long been reported (Lehmann, 1941; Conrad et al, 1964; Kruger and Schulze, 1956; Baile and Forbes, 1974). It is necessary to account for this in our model so that the contribution to the variation in DMI by other variables can be parsed more accurately. Dietary energy density (Mcal of NEm/kg of feed) has also been reported by many authors as a major determinant of DMI in ruminants (Blaxter, 1961; Crampton et al, 1957; Baumgardt, 1970).

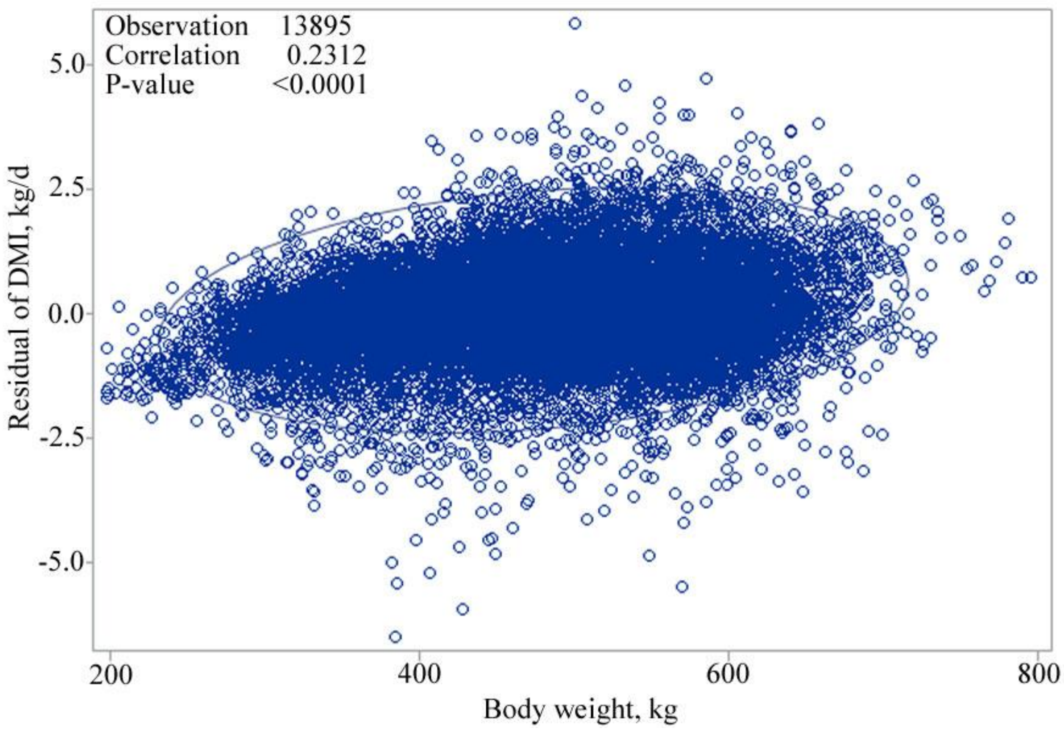

Figure 2.1. Scatter plot showing the relationship of residuals of DMI against BW

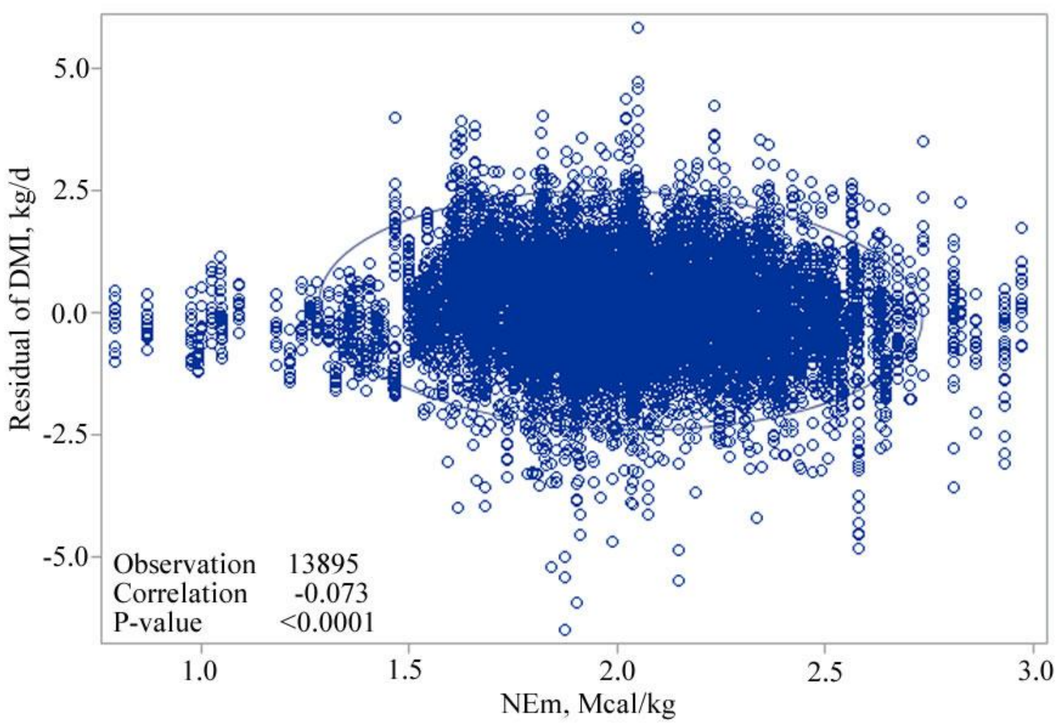

Figure 2.2. Scatter plot showing the relationship of residuals of DMI against dietary energy density (NEm, Mcal/kg)

2.5.2. Base Model, Ambient Temperature, and Solar Radiation

In our base model (Table 2.3), week of the year as a fixed effect, experiment as a random effect, linear effect of BW, quadratic effect of BW, linear effect of NEm and quadratic effect of NEm were included. Three forms of each weather variable were evaluated as a main effect independently of each other: the absolute weather variable, the two-week lag, and the monthly lag. It was expected that these three forms would be highly correlated. Only the most significant form of each weather variable was included because including more than one form of weather variable in the model would result in multicollinearity issues. Some other authors have reported similar approaches of handling multicollinearity by not including highly correlated variables to minimize multicollinearity issues (Appuhamy et al., 2014). Table 2.4 provides model summary statistics when fitting each variable independently of each other on the base model.

All three versions of ambient temperature were significant sources of variation, with the 2-week lag providing the best model fit statistics (Table 2.4). This can be attributed to the effect of temperature that the animals had previously been exposed, influencing the animal's current basal metabolism, thereby indirectly affecting current DMI (NRC, 1981). This is supported by the work of Fox and Tylutki (1998), who recommended that the average of the mean temperature that an animal has been exposed to over a month should be used to remove the day-to-day variation since temperature changes slowly from season to season. In our study, however, we prove that even 2-week lag of ambient temperature has higher influence than one-month lag. Model parameters when including the 2-week lag regressor are provided in Table 2.5.

Table 2.3. Variables in the base model

Variable[1]	Estimates	SE[2]	F-value	P-value
Week of the year			34.62	0.0001
Body weight, kg				
Linear	4.75×10^{-2}	2.27×10^{-3}	437.85	0.0001
Quadratic	-3.00×10^{-5}	2.27×10^{-6}	184.47	0.0001
Dietary NEm, Mcal/kg				
Linear	3.69×10^{0}	9.70×10^{-1}	14.55	0.0001
Quadratic	-1.31×10^{0}	2.43×10^{-1}	29.12	0.0001

1 Variables with 13,895 observations. AIC = Akaike information criterion (45,151) BIC = Bayesian information criterion (45,160).
2SE = Standard error.

It has been previously reported that environmental factors affect DMI and daily water intake (NRC, 1981). Hill and Wall (2017) reported that under high temperatures, livestock are expected to decrease DMI. Other factors like growth rate and size of cattle also affect DMI. Hill and Wall (2017) reported that thermoregulatory stress is better handled by efficient cattle compared to less efficient cattle because of better thermoregulatory ability of efficient cattle. For cold weather conditions, it is expected that DMI should increase, however, an apparent relationship between ambient temperature and DMI does not exist as reported by NRC (1981) because ambient temperature is most likely influenced by other variables. Mader et al. (2010) reported that the strength of relationship between ambient temperature and DMI by itself might be questioned because DMI is influenced by cattle type, body condition, management, and other environmental factors. In our study, we accounted for the variation that could be explained by BW, the dietary energy density, individual differences in the animal and the time of the year. All possible variations that may exist from the animal and the environment which are known to affect DMI were accounted for in the base model, however, there could be some other variable that affect DMI that were not accounted for.

Table 2.4. AIC, BIC, F and P values of each weather variable considered when added to the base model individually using maximum likelihood estimation method

Variable[1]	F-value	P-value	AIC[2]	BIC[3]
Base model			45,151*	45,160*
Absolute ambient temperature	28.82	0.0001	45,041	45,063
Two-week lag	55.52	0.0001	45,017	45,038
Monthly lag	27.52	0.0001	45,044	45,065
Absolute solar radiation	3.67	0.0553	45,065	45,087
Two-week lag	0.32	0.5703	45,068	45,090
Monthly lag	10.95	0.0009	45,058	45,080

[1]Variables with 13,895 observations. Units are oC for temperature and W/m2 for solar radiation.
[2]AIC = Akaike information criterion.
[3]BIC = Bayesian information.
*Restricted maximum likelihood estimation was used.

Table 2.5. Base model with two-week lag of ambient temperature

Variable[1]	Estimates	SE[2]	F-value	P-value
Week of the year			35.23	0.0001
Body weight, kg				
Linear	4.76×10^{-2}	2.27×10^{-3}	441.09	0.0001
Quadratic	-3.00×10^{-5}	2.27×10^{-6}	186.94	0.0001
Dietary NEm, Mcal/kg				
Linear	3.70×10^{0}	9.68×10^{-1}	14.58	0.0001
Quadratic	-1.31×10^{0}	2.43×10^{-1}	29.15	0.0001
Two-week lag of ambient temperature ˚C	-2.17×10^{-2}	2.91×10^{-2}	55.52	0.0001

[1]Variables with 13,895 observations. AIC = Akaike information criterion (45,017) BIC = Bayesian information criterion (45,038).
[2]SE = Standard error.

From the three solar radiation variables, only monthly lag of solar radiation was significant and improved model fit statistics compared to the base model (Table 2.4). Model parameters when including the monthly lag regressor are provided in Table 2.6. Solar radiation has been reported to have an influence on ambient temperature and heat loss from animals (Brosh et al., 1998). The sun angle changes daily and seasonally, which influences the thermal balance of the animal since exposed surface area and insulation are affected differentially (Keren and Olson, 2006). A perpendicularly standing animal to the sun's ray will absorb more short-wave radiation than one standing parallel to the sun (Clapperton et al., 1965). Factors such as sky conditions, ground cover and the shape and orientation of the animal's body also determines the amount of solar radiation absorbed (Keren, 2005). Prediction models used in the past did not examine the lag of solar radiation nor did they consider it separately, rather it was considered with other weather variables using an index named current effective temperature index (CETI) which accounts for temperature, humidity, wind speed and sunlight hours (Tedeshi and Fox, 2006). Mader et al. (2010) developed a comprehensive climate index (CCI) using ambient temperature while adjusting for relative humidity, wind speed and solar radiation. This type of index does not explain the effect of solar radiation or its lag on DMI since they were combined to form the CCI.

Models that utilized sunlight hours like the CETI Tedeshi and Fox, (2006) might not be appropriate since sunlight hours does not account for solar radiation absorbed by the environment and the animal's body which influences the thermal balance of the animal. It is more appropriate to measure and account for solar radiation that is being emitted by the sun and absorbed by the animal's body and the environment in DMI models.

Table 2.6. Base model with monthly lag of solar radiation

Variable[1]	Estimates	SE[2]	F-value	P-value
Week of the year			33.95	0.0001
Body weight, kg				
Linear	4.70×10^{-2}	2.27×10^{-3}	428.53	0.0001
Quadratic	-3.00×10^{-5}	2.27×10^{-6}	179.66	0.0001
Dietary NEm, Mcal/kg				
Linear	3.70×10^{0}	9.65×10^{-1}	14.71	0.0001
Quadratic	-1.31×10^{0}	2.43×10^{-1}	29.40	0.0001
Monthly lag of solar radiation W/m^2	-3.20×10^{-3}	9.67×10^{-4}	10.95	0.0009

[1]Variables with 13,895 observations. AIC = Akaike information criterion (45,058) BIC = Bayesian information criterion (45,080).
[2]SE = Standard error.

When the main effect of two-week lag of ambient temperature and monthly lag of solar radiation were included in the model, only two-week lag of ambient temperature was significant (P <0.005) in the model (Table 2.7). Although, the main effect of monthly lag of solar radiation was not significant when considered with two-week lag of ambient temperature, it was significant when included in the model alone. This prompted us to examine further if an interaction between these two variables exists.

Table 2.7. Base model with two-week lag of ambient temperature and monthly lag of solar radiation

Variable[1]	Estimates	SE[2]	F-value	P-value
Week of the year			34.92	0.0001
Body weight, kg				
Linear	4.74×10^{-2}	2.27×10^{-3}	434.66	0.0001
Quadratic	-3.00×10^{-5}	2.28×10^{-6}	183.97	0.0001
Dietary NEm, Mcal/kg				
Linear	3.70×10^{0}	9.67×10^{-1}	14.60	0.0001
Quadratic	-1.31×10^{0}	2.43×10^{-1}	29.20	0.0001
two-week lag of ambient temperature	-2.07×10^{-2}	3.06×10^{-3}	45.63	0.0001
Monthly lag of solar radiation	-1.05×10^{-3}	1.01×10^{-3}	1.07	0.3012

[1]Variables with 13,895 observations. Units are ˚C for temperature and W/m^2 for solar radiation. AIC = Akaike information criterion (45,018) BIC = Bayesian information criterion (45,040).
[2]SE = Standard error.

When the interaction between two-week lag of solar radiation and monthly lag of solar radiation was included in the model while retaining the main effects of each, the P-values of the three relationships changed to 0.25, 0.78 and 0.0074 for two-week lag of ambient temperature, monthly lag of solar radiation and their interaction, respectively (Table 2.8).

The BIC values were reduced by 5 points which explains that the interaction made a significant impact on the model fit. The main effects becoming insignificant could be because of a cancellation effect that the main effects and the interactions had on each other.

Table 2.8. Base model, two-week lag of ambient temperature and monthly lag of solar radiation and their interaction using maximum likelihood estimation

Variable[1]	Estimates	SE[2]	F-value	P-value
Week of the year			32.92	0.0001
Body weight, kg				
Linear	4.75×10^{-2}	2.28×10^{-3}	435.37	0.0001
Quadratic	-3.00×10^{-5}	2.28×10^{-6}	183.98	0.0001
Dietary NEm, Mcal/kg				
Linear	3.69×10^{0}	9.68×10^{-1}	14.56	0.0001
Quadratic	-1.31×10^{0}	2.43×10^{-1}	29.13	0.0001
two-week lag of ambient temperature	-6.91×10^{-3}	6.00×10^{-3}	1.33	0.2494
Monthly lag of solar radiation	3.08×10^{-4}	1.14×10^{-3}	0.07	0.7867
two-week lag of ambient temperature × Monthly lag of solar radiation	-1.4×10^{-4}	5.2×10^{-5}	7.18	0.0074

[1]Variables with 13,895 observations. Units are ˚C for temperature and W/m^2 for solar radiation. AIC = Akaike information criterion (45,013) BIC = Bayesian information criterion (45,035)
[2]SE = Standard error.

Interestingly, when only the interaction between two-week lag of ambient temperature and monthly lag of solar radiation were added to the base model, the interaction was highly significant (P=0.0001), and the AIC and BIC values were lower which signifies that the model was improved and has a better model fit (Table 2.9; Figure 2.3). This better model fit indicates that solar radiation is important and could better explain the variation in DMI than just absolute temperature alone. Others (Bakken, 1981; Tedeshi and Fox, 2006; Mader et al., 2010) have considered ambient temperature and some weather variables together, combining them into an index. This shows that multiple weather variables interact together to affect DMI suggesting that combining weather variables into an index should be discouraged.

Table 2.9. Base model and interaction between two-week lag of ambient temperature and monthly lag of solar radiation using restricted maximum likelihood estimation method (Final Model)

Variable[1]	Estimates	SE[2]	F-value	P-value
Intercept	-6.23×10^{0}	1.26×10^{-0}		0.0008
Week of the year			33.71	0.0001
Body weight, kg				
Linear	4.74×10^{-2}	2.27×10^{-3}	434.78	0.0001
Quadratic	-3.00×10^{-5}	2.27×10^{-6}	182.89	0.0001
Dietary NEm, Mcal/kg				
Linear	3.69×10^{0}	9.67×10^{-1}	14.47	0.0001
Quadratic	-1.31×10^{0}	2.43×10^{-1}	28.99	0.0001
Two-week lag of ambient temperature × Monthly lag of solar radiation	-1.80×10^{-4}	2.3×10^{-5}	61.92	0.0001

[1]Weather variable units are ˚C for temperature and W/m² for solar radiation AIC = Akaike information criterion (45,113) BIC = Bayesian information criterion (45,121).
[2]SE = Standard error.

Since the interaction between two-week lag of ambient temperature and monthly lag of solar radiation gave a better model fit, the interaction was left in the model while their main effects were removed. NASEM (2016) reported that solar radiation accentuates the effect of temperature. In our model, solar radiation accentuated the effect that low and high temperature had on DMI. Interestingly, in Figure 2.3 it can be observed that, with increasing temperature and reduction in solar radiation, DMI decreased.

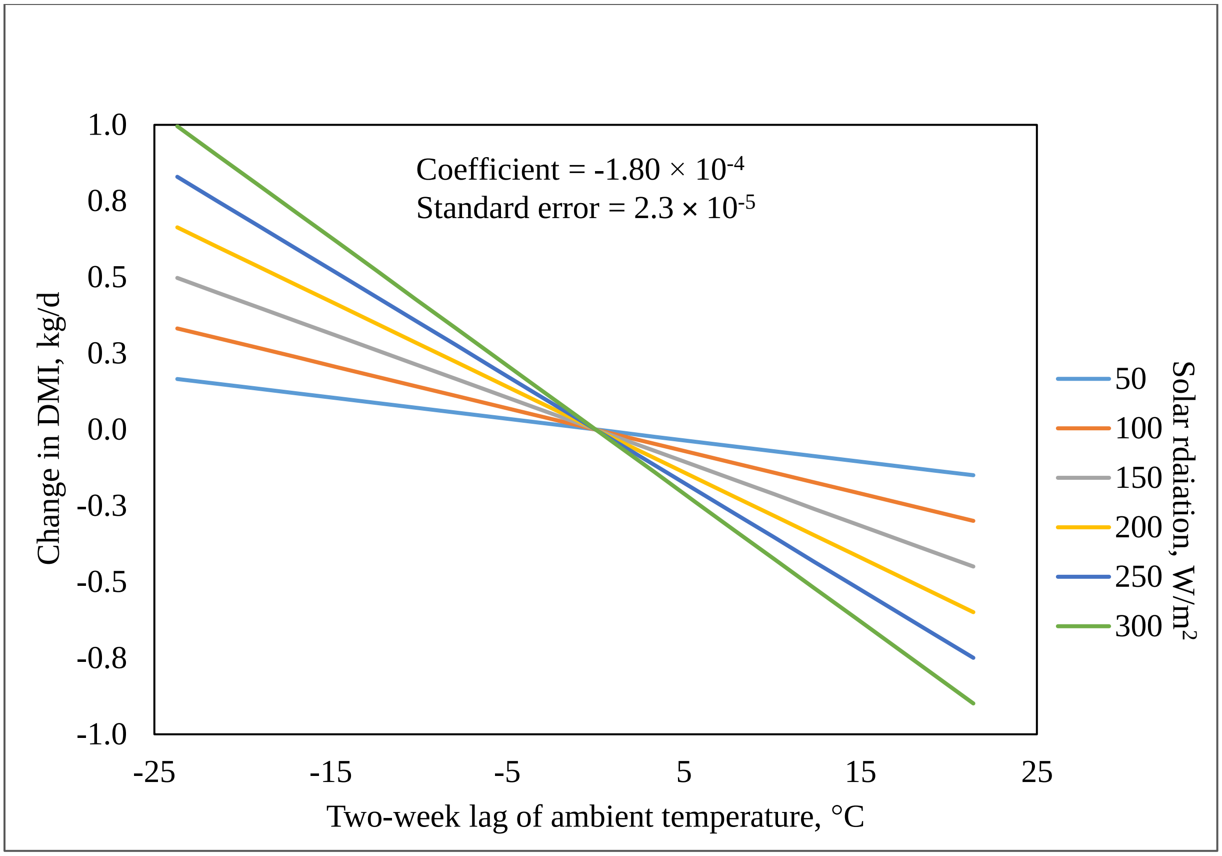

Figure 2.3. The interaction between two-week lag of ambient temperature and monthly lag of solar radiation and their influence on DMI

This could be attributed to the interaction between temperature and solar radiation and how they influence each other. This indicates that on cloudy days with high temperature, DMI decreases but on sunny days with extremely low temperature, DMI increases. In extreme cold temperatures, the NEm requirement of cattle increases linearly and, therefore, the animal will need to increase its energy intake from feed to meet the requirement for increased heat production and maintenance of homeostasis. There is a dearth of information on the effect of solar radiation on animals in extremely cold weather conditions. Most reported studies examined the effect of solar radiation on animals in warm to hot weather (Mader et al., 2006 Mader at al., 2010; Melton et al, 2018; Lee et al., 2019). Studies that examined the effect of cold weather conditions on animals (Siple and Passel, 1945) did not examine the effect of solar radiation on

DMI. Siple and Passel (1945) developed a windchill index (WCI), relating ambient temperature (Ta) and wind speed (WS) to the time for freezing water for cold conditions. Mader et al. (2006) developed adjustments to the THI based on panting scores and measures of wind speed and solar radiation but only had two studies conducted in cold weather conditions in the data they examined. Olson (1938) examined the effect of sunlight on dairy cattle that were exposed to sunlight or without sunlight. The no-sunlight group had better growth than the sunlight group because the sunlight group were housed outside and maintained under cold winter conditions, the diet was also restricted to amount consumed by the no sunlight group. This corroborates the effect of extreme cold weather on energy requirements and growth. If the intake of the animal does not increase to meet the energy demand for heat production, and maintenance of homeostasis in extremely low ambient temperature, growth performance is compromised. On the other hand, under high ambient temperatures, livestock are expected to have decreased DMI to reduce their metabolic heat production. Mader et al. (2010) reported that solar radiation and ambient temperature have a linear relationship, which is similar with what we observed in this study. Heat input from metabolic heat production and solar radiation, and heat output from evaporative and non-evaporative avenues are the factors that determine body temperature in cattle (Brosh et al., 1998). As temperature decreased to below the lower critical temperature, the animal becomes cold stressed, and the maintenance energy requirement increases. Donald (1988) reported that animals under severe cold stress tend to have reduced intake. However, in this study, DMI increased with increasing solar radiation and reduction in temperature. This may be because of the effect of solar radiation in neutralizing the cold stress on the animal thereby not making them extremely cold stressed to the point of losing weight, but cold enough to increase DMI to combat the cold stress towards the thermoneutral zone. Olson and Wallander (2002) reported that during extreme cold weather, cattle spent more time standing to maximize heat gain from solar radiation instead of minimizing energy expended by laying down. This is similar to what we believe the animals used in this study experienced in which solar radiation contributed to heat gain to make the animals more comfortable and active hence the increase in DMI.

Sevi et al (2001) examined the effect of solar radiation on Comisana ewes. They reported that solar radiation and the interaction between solar radiation and feeding time had significant effect on rectal temperatures. This indicates that solar radiation influences thermal balance, energy metabolism and could be attributed to the change in DMI at different intensities of solar radiation. Solar radiation has been reported to directly affect the surface an animal has contact with as well as the temperature of the animal, especially in dark-hided cattle (Mader et al., 2006).

Kennedy et al. (1986) reported that in cold weather, ruminal motility and digesta passage increases thereby increasing DMI. NASEM (2016) reported that other adverse weather conditions can increase the effects of ambient temperature. However, the response to temperature varies between animals (Young, 1981). The observed increase in DMI as two-week lag of temperature decreases, and monthly lag of solar radiation increases could, also be attributed to the long-term effect of solar radiation on melatonin. Light inhibits melatonin secretion by inhibiting the production of N-acetyltransferase, the primary enzyme for melatonin synthesis (Hickman et al., 1999). Melatonin slows down metabolism, increases fat deposition and decreases feed intake and ultimately productivity of animals. With more light and solar radiation, we speculate that this caused a reduction of melatonin secretion over time and therefore triggered increased feed intake. However more research is needed on the relationships between solar radiation, melatonin secretion, DMI, and growth.

2.6. Conclusion

To summarize, our results showed that variation in DMI was better explained by having the interaction between two-week lag of ambient temperature and monthly lag of solar radiation in the prediction model as opposed to ambient temperature alone. This indicates that solar radiation could be a good predictor and explain some variation in DMI occurring because of thermal effects. The model developed in this study could be better than models that used THI or CCI as an index rather than considering individual weather variables and/or their interactions.

2.7. Implications

Changes in solar radiation and temperature were associated with changes in DMI and there was an interaction between them. These variables are important and should be considered in DMI prediction equations. Beef cattle adjust their DMI in response to adverse weather conditions. DMI is influenced by several factors and how cattle respond to changes in DMI is highly variable varying from individual to individual. Understanding more variables that influence DMI will help in increasing the accuracy of DMI prediction models which will in turn assist producers and feedlot managers to estimate the quantity of feed they need for their beef cattle. It will be necessary to examine how other weather variables like windspeed and dewpoint may interact with temperature and solar radiation to influence DMI and ADG.

2.8. Literature Cited

Baile C. A., and J. M Forbes. 1974. Control of feed intake and regulation of energy balance in ruminants. Physiol. Rev. 54:160-214. DOI: 10.1152/physrev.1974.54.1.160

Bakken. G. S. 1981. How many equivalent black-body temperatures are there? J. Therm. Biol., 6 pp. 59-60 DOI: 10.1016/0306-4565(81)90045-0

Blaxter, K. L. 1961. Efficiency of feed conversion by different classes of livestock in relation to food production. Fed. Proc.20: 68.

Brobeck, J. R. 1948. Food intake as a mechanism of temperature regulation. Yale J. Biol. Med. 20:545-552

Brosh A., Aharoni, A. A., Degen, A. A., Wright, D., and B. A. Young. 1998. Effects of Solar radiation, dietary energy, and Time of Feeding on Thermoregulatory Responses and Energy Balance in Cattle in a Hot Environment. J. Anim. Sci. 1998. 76:2671–2677 DOI: 10.2527/1998.76102671x

Clapperton, J., J. P. Joyce, and K. L. Blaxter. 1965. Estimates of the contribution of solar radiation to the thermal exchanges of sheep at a latitude of 55° north. J. Agric. Sci. (Cambridge), 64:37-49

Collier, R. J., L. H. Baumgard, R. B. Zimbelman, and Y. Xiao Z. 2019. Heat stress: Physiology of acclimation and adaptation Anim. Front., 9, 12-19 DOI: 10.1093/af/vfy031

Conrad, H. R., A. D. Pratt, and J. W Hibbs. 1964. Regulation of feed intake in dairy cows; change in importance of physical and physiological factors with increasing digestibility. J. Dairy Sci. 47: 54-62 DOI:10.3168/jds.S0022-0302(64)88581-7

Donald G. Wagner. 1988. Effects of Cold Stress on Cattle Performance and Management Factors to Reduce Cold Stress and Improve Performance. The Bovine Practitioner 23: 88-92 https://doi.org/10.21423/bovine-vol0no23p88-93

Fox, D. G., and T. P Tylutki. 1998. Accounting for the effects of environment on the nutrient requirements of dairy cattle. J. Dairy Sci. 81:3085-3095 DOI: https://doi.org/10.3168/jds.S0022-0302(98)75873-4

Hahn G. L 1999. Dynamic responses of cattle to thermal heat loads. J. Anim. Sci. 77 (Suppl. 2):10 20 DOI: 10.2527/1997.77suppl_210x

Hickman, A. B., D. C. Klein, and F. Dyda. 1999. Melatonin Biosynthesis: The Structure of Serotonin N-Acetyltransferase at 2.5 Å Resolution Suggests a Catalytic Mechanism. Molecular Cell, 3:23–32 DOI: 10.1016/s1097-2765(00)80171-9

Hill, D. L., and Wall E. 2017. Weather influences feed intake and feed efficiency in a temperate climate. J. Dairy Sci. 100:2240-2257 DOI: 10.3168/jds.2016-11047

Islas, A., T. C. Gilbery, R. S. Goulart, C. R. Dahlen, M. L. Bauer, and K. C. Swanson. 2014. Influence of supplementation with corn dried distillers grains plus solubles to growing calves fed medium-quality hay on growth performance and feeding behavior. J. Anim. Sci. 92:705-71 DOI: 10.2527/jas.2013-7067

Keren, E. N., and B. E Olson. 2006. Thermal balance of cattle grazing winter range: Model development. J. Therm. Biol. 31:371-377 DOI: 10.2527/2006.8451238x

Keren, I. N. 2005. “Thermal balance model for cattle grazing winter range”. Master’s thesis submitted to the department of Animal and Range Sciences, Montana State University, Bozeman, MT. p. 9

Kim, J. H. 2019. Multicollinearity and misleading statistical results. Korean J. Anesthesiology, 72:558–569. DOI: https://doi.org/10.4097/kja.19087

Kruger, L., and G. Schulze. 1956. Uber futteraufnahme und Verzehrleistungen bei Milchkuhen II. Die sattigungsbewertung der Futtermittel. Zuch tungskunde 28: 438-450

Lees, A. M., Sejian, V., Wallage, A. L., Steel, C. C., Mader, T. L., Lees, J. C., and J. B. Gaughan. 2019. The impact of heat load on cattle. Animals. 9:322. https://doi.org/10.3390/ani9060322

Lehmann F. 1941. Die lehre vom Ballast. Z. Tierphysiol. Teirnahr. Futtermittelk 5:155-173.

Lofgreen, G. P., and W. N. Garett. 1968. A system for expressing net energy requirements and feed values for growing and finishing beef cattle. J. Anim. Sci. 27:793-806 DOI: https://doi.org/10.2527/jas1968.273793x

Mader, T. L., L. J. Johnson, and J. B. Gaughan. 2010. A comprehensive index for assessing environmental stress in animals. J. Anim. Sci. 88:2153-2165. DOI: 10.2527/jas.2009-2586

Mader, T. L., M. S. Davis, and T. Brown-Brandl. 2006. Environmental factors influencing heat stress in feedlot cattle. J. Anim. Sci. 84:712–719. DOI: 10.2527/2006.843712x

Melton B. M., T. Winders, B. M. Boyd, C. N. Macken, A. K. Watson, J. C. MacDonald, and G. G. Erickson. 2018.Impact of Shade on Performance, Body Temperature, and Heat Stress of Finishing Cattle in Eastern Nebraska. 10th International Livestock Environment Symposium (ILES X) DOI: https://doi.org/10.13031/iles.18-098

Montanholi, Y. R., K. C. Swanson, R. Palme, F. S. Schenkel, B. W. McBride, D. Lu, and S. P. Miller. 2010. Assessing feed efficiency in beef steers through feeding behavior, infrared thermography and glucocorticoids. Animal 4:692-701. DOI: 10.1017/S1751731109991522

Nakamura, K. and S. F Morrison. 2008. A thermosensory pathway that controls body temperature. Nat. Neurosci. 11:62-71. DOI: 10.1038/nn2027

National Academies of Science, Engineering, and Medicine. 2016. Nutrient requirements of beef cattle, 8th Rev. Ed. Washington DC: The National Academies.

North Dakota Agricultural weather station (NDAWN). 2021. https://ndawn.ndsu.nodak.edu/. [Accessed January 15, 2021]

NRC. 1981. Effect of Environment on Nutrient requirements of Domestic Animals. National Academy Press, Washington, DC.

Olson, B. E., and R. T. Wallander. 2002. Influence of winter weather and shelter on activity patterns of beef cows. Canadian Journal of Animal Science. 82: 491-501. DOI: https://doi.org/10.4141/A01-070

Olson, T. M. 1938. Effect of sunlight on the growth, production, and reproduction of dairy cattle. Bulletins. Paper 319. http://openprairie.sdstate.edu/agexperimentsta_bulletins/319

SAS User’s Guide: Statistics. 2004. SAS Institute Inc., Cary, NC.

Sevi, A., Annicchiarico, G., Albenzio, M., Taibi, L., Muscio, A., and S. Dell’Aquila. 2001. Effects of solar radiation and feeding time on behavior, immune response, and production of lactating ewes under high ambient temperature. J. Dairy Sci. 84: 629–640. DOI: https://doi.org/10.3168/jds.S0022-0302(01)74518-3

Siple, P. A. and C. F. Passel, 1945. Measurements of Dry Atmospheric Cooling in Subfreezing Temperatures. Proceedings of the American Philosophical Society. 89:177-199.

Stevens, J. P. 2007. Intermediate statistics: A modern approach. 3rd Ed. New York, NY: Routledge.

Swanson, K. C., A. Islas, Z. E. Carlson, R. S. Goulart, T. C. Gilbery, and M. L. Bauer. 2014. Influence of dry-rolled corn processing and increasing dried corn distillers grains plus solubles inclusion for finishing cattle on growth performance and feeding behavior. J. Anim. Sci. 92:2531-2537. DOI: 10.2527/jas.2013-7547

Tedeshi, L. O., and Fox D. G. 2006. The ruminant nutrition System: An applied model for prediction nutrient requirements and feed utilization in ruminants. Xan Edu, Acton, MA. p. 285

Thornton, P. K., J. Van de Steeg, A. Notenbaert, and M. Herrero. 2009. The impacts of climate change on livestock and livestock systems in developing countries: A review of what we know and what we need to know. Agric. Syst. 101:113-127 DOI: https://doi.org/10.1016/j.agsy.2009.05.002

Young B. A. 1981. Cold stress as it affects animal production. J. Anim. Sci. 52:154 DOI: 10.2527/jas1981.521154x

Zinn, R. A., and Y. Shen. 1998. An evaluation of ruminally degradable intake protein and metabolizable amino acid requirements of feedlot calves. J. Anim. Sci. 76:1280-1289 DOI: 10.2527/1998.7651280x

CHAPTER 3. UNDERSTANDING THE RELATIONSHIP BETWEEN WEATHER VARIABLES AND DRY MATTER INTAKE (DMI) IN BEEF STEERS

3.1. Abstract

The relationship between weather variables and dry matter intake (DMI) in beef steers was examined using daily intake data from 790 beef steers collected through an Insentec feeding system. Daily data was condensed into weekly averages (n = 13,895 steer-weeks). The variables considered for this study were DMI (2.50 to 23.60 kg/d), body weight (197.3 to 796.1 kg), dietary energy density (NEm; 0.793 to 2.970 Mcal/kg), absolute ambient temperature (-23.7 to 21.4 °C), range of temperature (2.8 to 19.4 °C), dew point (-27.8 to 14.3 °C), wind speed (2.08 to 6.49 m/s), solar radiation (30.8 to 297.1 W/m^2), and two-week lag (average of previous two week’s values) and monthly lag (average of previous four week’s values) of each weather variable listed. The MIXED procedure of SAS with Toeplitz variance-covariance structure was used to determine the final model to predict DMI, while accounting for the effects of body weight, NEm and other variables in the model. Significant amount of weather variables explained the variation in DMI. Ambient temperature interacted ($P \leq 0.005$) with range of temperature, wind speed, solar radiation, and dew point. Other interactions ($P = 0.0001$) between weather variables were the interaction between range of temperature vs. dew point and wind speed vs. solar radiation. This study shows the important weather variables that affect DMI of beef steers and will help in improving the accuracy of the DMI prediction equations for beef cattle.

3.2. Introduction

Overall performance of animals depends on the amount of energy they consume and how effectively they utilize this energy for maintenance and subsequently growth. Utilization of energy consumed is affected by the environment because animals generally interact with their environment as homeotherms (Hahn, 1999). Weather can greatly affect the bioenergetics of animals, which in turn can have adverse effects on the performance and wellbeing of livestock. In most cases, extreme weather conditions could lead to either reduced or elevated feed intake, reduced efficiency, or reproduction (NRC, 1981). Livestock producers need a better understanding of how weather variables impact their animals and how the animals respond to weather extremes. This will enable livestock producers to make improved decisions on strategies and ways to reduce losses during changes in weather (Hahn, 1999). For beef producers to have a profitable enterprise, they need to optimize the dry matter intake (DMI) consumption of their animals. DMI as reported by Anele et al. (2014) is the single most important factor influencing productivity in growing-finishing beef cattle operations. Since DMI is very important in beef cattle operations, predicting and measuring DMI accurately is cardinal in knowing the nutrient requirements of animals, formulating and balancing diets, and ultimately predicting performance based using net energy equations (NRC, 1996). If producers can accurately measure or predict DMI, they could better manage the feed resources and ensure adequate availability of feed for their animals.

The current models used in predicting DMI in beef cattle are the equations proposed by the Agricultural Research Council (ARC, 1980), the Cornell Net Carbohydrate and Protein System (Fox et al., 2004), the NRC (2001) and most recently, NASEM (2016). However, these equations do not fit the Northern Great Plains of the United States where temperature can go below -30°C in the winter (Block et al., 2001). At the same time some of the prediction equations do not account for other weather variables that may affect DMI. In most of the models, relative humidity has been used. Relative humidity is dependent on temperature and can be misleading

(National Weather Service, 2021), for this reason dewpoint might be a more accurate predictor to estimate the amount of moisture in the air. The previous models also do not consider the lag of weather variables and some weather variables do not have a direct impact on animals immediately, as it may take some time for some of their effects to manifest, for this reason, it will be beneficial to know how the lag in weather variables could have an impact on DMI.

The objective of this study is to examine how absolute, two-week lag and monthly lag of weather variables (solar radiation, dewpoint, ambient temperature, range of temperature, and windspeed) affects DMI. This could help in understanding and estimating DMI intake more accurately.

3.3. Materials and Methods

3.3.1. Data Collection

Data used for this experiment were collected from the Beef Cattle Research Complex of North Dakota State University, Fargo, North Dakota located at latitude 46.9027853 degrees North and longitude -96.8418183 degrees West. An Insentec feeding system (RIC feeding system; Hokofarm Group, Marknesse, The Netherlands), which records the amount of feed intake, number of visits, time of visit and meals for each animal, was used for the data collection. The data used were from 10 experiments that were conducted between 2011 and 2017 (Table 3.1).

Table 3.1. Experiments used in this study

Year (week of the year)		n[1] of steers	n of steer-week observations	Breed[2]	Publication
Start	End				
2011 (wk. 45)	2012 (wk. 4)	67	804	AN, SM, and SH	Islas et al., 2014
2012 (wk. 46)	2013 (wk. 5)	94	1120	AN, SM, and SH	Prezotto et al., 2017
2012 (wk. 10)	2012 (wk. 22)	63	819	AN, SM, and SH	Swanson et al., 2014
2013 (wk. 6)	2013 (wk. 22)	66	1098	AN, SM, and SH	Swanson, et al., 2017a
2013 (wk. 38)	2014 (wk. 5)	113	2260	AN-crossbred	Swanson et al., 2018
2014 (wk. 11)	2014 (wk. 22)	44	527	AN, SM, and SH	Swanson et al., 2017a
2014 (wk. 4)	2014 (wk. 22)	81	1339	AN, SM, and SH	Rodenhuis et al., 2017
2015 (wk. 51)	2016 (wk. 18)	61	1211	AN, SM, and SH	Knutson et al., 2020
2016 (wk. 45)	2017 (wk. 20)	134	3432	AN, SM, and SH	Sitorski et al., 2019
2017 (wk. 46)	2018 (wk. 11)	67	1285	AN and SM	Trotta et al., 2019

[1]n=number.
[2]AN = Angus, SM = Simmental, SH = Shorthorn.

3.3.2. Weather Data

Data for weather variables were obtained from the North Dakota Agricultural Weather Network (NDAWN) station for each experiment period included in this study. Each NDAWN station is assumed to adequately represent all weather conditions, except rainfall, in a 32 km radius (NDAWN, 2021). The NDAWN station, which is 2.33 km from the BCRC, provides five-minute averages, hourly averages, daily, monthly, and yearly summaries for each supported weather variable (NDAWN, 2021). For this study, daily summaries of each weather variable were used for each experiment period included.

Weather variables modeled for this study included:

- Ambient temperature: the air temperature of the surrounding environment (˚C)
- Absolute range in temperature: the difference between absolute minimum and absolute maximum temperature

- Dew point: the temperature at which water vapor in the air begins condensing to form liquid. The dew point temperature is calculated from the air temperature and relative humidity. (NDAWN, 2021).
- Wind speed: average of all measured wind speeds during the hour for a period of 24 hours). Wind speed is measured every 5 seconds 10 meters above the soil surface with an anemometer (NDAWN, 2021).
- Solar radiation: total of all hourly totals of incident solar radiation energy for a 24-hour period from midnight to midnight (W/m2) (NDAWN, 2021). Total incident solar radiation flux density is measured in Watts/m2 at approximately 2 m above the soil surface with a pyranometer.
- The two-week lag and monthly lag of each weather variable was also considered. Two-week lag is the average of the previous two week's weather variable while monthly lag is the average of the previous month's weather variable in question.

3.3.3. Non-Weather Variables

The non-weather variables considered for this experiment include weekly average daily dry matter intake (DMI), weekly average body weight (BW), dietary net energy of maintenance (NEm), experiment, and the week of the year. Week of the year ranged from week 1 to 22 and week 30 to 52. In this study, only 1 experiment had observations for weeks 23 to 29 which will result in inadequate sample and cause scaling issues if they were included in models.

3.3.4. Data Management

The daily feed intake data was averaged into weekly averages to reduce the day-to-day fluctuation. The weekly dry matter analysis of the diet fed from each experiment was matched with the weekly feed intake to calculate the actual DMI consumed by each animal. Weekly BW for each animal was calculated from the monthly BW data values by using simple linear regression. Values for weather variables were converted into weekly averages. Dietary energy density (NEm,) was calculated by using the equation of Lofgreen and Garrett (1968) and Zinn and Chen (1998) using initial BW, final BW, average daily gain (ADG) and average DMI. The descriptive statistics of the variables used in this study is shown in Table 3.2.

Table 3.2. Descriptive statistics of the variables used for this study

Variable[1]	Mean	Minimum	Maximum	SD[2]	SE[3]
BW, kg[4]	474.18	197.31	796.06	99.04	0.84
DMI, kg/d[4]	10.69	2.50	23.60	2.76	0.02
NEm, Mcal/kg[4]	2.01	0.79	2.97	0.30	0.00
Ambient temperature, ˚C					
No lag[4]	-2.01	-23.73	21.40	10.45	0.09
Two-week lag[4]	-2.19	-20.73	23.56	9.58	0.08
Monthly lag[4]	-2.24	-17.95	22.74	9.05	0.08
Solar radiation, W/m^2					
No lag[4]	112.51	30.81	297.12	64.00	0.54
Two-week lag[4]	107.00	34.56	271.98	58.57	0.50
Monthly lag[4]	104.22	43.66	256.57	54.31	0.46
Wind speed, m/s					
No lag	3.85	2.08	6.49	0.72	0.01
Two-week lag	3.85	2.34	4.96	0.52	0.00
Monthly lag	3.83	2.79	4.64	0.40	0.00
Range of temperature, ˚C					
No lag	10.46	2.79	19.43	2.66	0.02
Two-week lag	10.27	4.57	15.80	2.24	0.02
Monthly lag	10.18	5.94	15.02	1.76	0.01
Dew point, ˚C					
No lag	-7.00	-27.84	14.34	8.89	0.08
Two-week lag	-6.97	-24.59	16.96	8.12	0.07
Monthly lag	-6.92	-21.61	14.94	7.68	0.07

[1] Variable with 13, 895 observations.
[2]SD=Standard error.
[3]SE=Standard deviation.
[4]Data also shown on Table 2.2.

3.4. Statistical Analysis

Data were analyzed using the MIXED procedures of (SAS Inst., Cary, NC) and within-individual relationship was accounted for using the Toeplitz covariance structure. Week of the year was used as fixed effect and experiment was included as a random effect to output the residuals. Correlation among weather variables was checked using the PROC CORR statement of SAS. Linear and quadratic effects of all the weather variables modeled were tested.

The model for fitting residuals, the base model and the final model were analyzed using the restricted maximum likelihood estimation method (REML), while the maximum likelihood (ML) was used in each step of the stepwise addition or removal of variables. Akaike information criterion (AIC) and Bayesian information criterion (BIC) values were used to assess model fit each time a variable was added or removed from the model in a stepwise fashion. The parameter estimates were outputted using the solution statement. The full model was refitted using REML to obtain less biased estimates. For all the models, components with ($P < 0.05$), F-values, and their respective AIC and BIC values are reported.

3.5. Results and Discussion

3.5.1. Base Model

In our base model (Table 3.3), week of the year (fixed effect), experiment (random effect), linear effect of BW, quadratic effect of BW, linear effect of NEm and quadratic effect of NEm were included. The AIC and BIC values for the base model were 45,151 and 45,160, respectively. Three forms of each weather variable were evaluated: the absolute weather variable, the two-week lag, and the monthly lag. Only the most significant form of each weather variable was included because including more than one form of weather variable in the model would result in multicollinearity issues. Some other authors have reported similar approaches of handling multicollinearity by not including highly correlated variables to minimize multicollinearity issues (Appuhamy et al., 2014).

Table 3.3. Variables in the base model

Variable[1]	Estimates	SE[2]	F-value	P-value
Week of the year			34.62	0.0001
BW, kg				
Linear	4.75×10^{-2}	2.27×10^{-3}	437.85	0.0001
Quadratic	-3.00×10^{-5}	2.27×10^{-6}	184.47	0.0001
Dietary NEm, Mcal/kg				
Linear	3.69×10^{0}	9.70×10^{-1}	14.55	0.0001
Quadratic	-1.31×10^{0}	2.43×10^{-1}	29.12	0.0001

[1]Variable with 13,895 observations. AIC = Akaike information criterion (45,151), BIC = Bayesian information criterion (45,160).
[2]SE = standard error.

3.5.2. Ambient Temperature Predictors with Base Model

The result of predictor variables when added to the base model individually are shown (Table 3.4). Two-week lag of ambient temperature improved the model fit better compared to absolute ambient temperature and monthly lag of ambient temperature. NRC (1981) reported that the previous temperature an animal has been previously exposed to influences the current metabolism of the animal which affects its current DMI. In cold situations, as obtainable in the Northern Great Plains of North America, the initial response is increasing metabolic heat production, which is achieved by increasing DMI, but as long exposure of cold continues, it gradually results in adaptive responses through physiological and morphological changes, (NRC, 1981). There is a trend for intake to increase to at least -15°C as temperature decreases (NRC, 1981). NRC (1981) reported that in some cases, DMI reduces as temperature reduces because the time spent feeding reduces as the animal spends less time feeding because of standing to shiver. NRC (1981) reported that under feedlot conditions in Canada during mid-winter, daily gain of steers decreases by 70 percent when temperature reached -17°C. NRC (1981) concluded that with temperature above 25°C and below -10°C, type of ration and temperature level affects DMI, but with temperature between 0 to 25°C, digestibility of ration is more important than ambient temperature.

Table 3.4. AIC, BIC, F and P values of each weather variable considered when added to the base model individually

Variable[1]	F-value	P-value	AIC[2]	BIC[3]
Base model	-	-	45,151	45,160
Ambient temperature				
No lag	28.82	0.0001	45,041	45,063
Two-week lag	55.52	0.0001	45,017	45,038
Monthly lag	27.52	0.0001	45,044	45,065
Solar radiation				
No lag	3.67	0.0553	45,065	45,087
Two-week lag	0.32	0.5703	45,068	45,090
Monthly lag	10.95	0.0009	45,058	45,080
Range of temperature				
No lag	0.63	0.4287	45,068	45,089
Two-week lag	94.84	0.0001	44,981	45,002
Monthly lag	77.52	0.0001	44,955	45,017
Wind speed				
No lag	21.15	0.0001	45,048	45,070
Two-week lag	4.15	0.0416	45,065	45,086
Monthly lag	44.58	0.0001	45,028	45,049
Dew point				
No lag	13.32	0.0003	45,056	45,077
Two-week lag	32.16	0.0001	45,038	45,060
Monthly lag	8.62	0.0033	45,061	45,082

[1]Variable with 13,895 observations. Units are °C for ambient temperature, range of temperature and dew point, m/s for wind speed and W/m^2 for solar radiation.
[2]AIC = Akaike information criterion.
[3]BIC = Bayesian information criterion.

3.5.3. Solar Radiation Predictors with Base Model

Monthly lag of solar radiation was the only significant (P = 0.0001) variable that gave the best model fit compared with absolute solar radiation and two-week lag of solar radiation when included alone in the base model. Solar radiation has been reported to affect DMI in animals

(Hill and Wall, 2017). Bourke (2008) reported that in cattle, exposure to sunlight causes an increase in body temperature which can be attributed to solar radiant heat. This increase in temperature affects the thermobalance of the animal which subsequently affects DMI. Radiation from the sun absorbed by the animal's body depends on the sky condition, ground cover and the animal's body orientation relative to the sun. Hill and Wall (2017) examined how feed intake and feed efficiency vary in response to weather conditions in Holstein Friesian cows utilizing 73,000 daily feed intake and feed efficiency records from cows over an 8-year period in the United Kingdom. Hill and Wall (2017) reported that cows had decreased DMI as temperature humidity index increased. The temperature humidity index used in the study by Hill and Wall (2017) accounted for wind speed and solar radiation. In their study, they also reported that maximum likelihood models testing for the effects of THI with wind speed and solar radiation explained feed intake and feed efficiency better than models testing for THI_{adj} or comprehensive climate index (CCI). Some authors have reported that solar radiation and velocity of ambient air temperature (which affects rates of latent and sensible heat load) influence the thermal tolerance of cattle (Dikmen and Hansen, 2009; Graunke et al., 2011; Hammami et al., 2013). Mader et al (2010) validated the effect CCI which was developed to account for the effect of cold and hot climates on cattle. The CCI uses ambient temperature that is adjusted for solar radiation, wind speed and relative humidity. Why monthly lag of solar radiation was the best explanatory variable for DMI when compared with absolute and two-week lag of solar radiation when included alone in the model could be attributed to the fact that weather variables could have a delayed effect on biological traits and the duration of the weather event determines the effects it has on the animal (Renaudeau et al., 2012; Hill and Wall, 2015). Also, average over 28 days might be better than 14 days or 1 day.

3.5.4. Range of Temperature Predictors with Base Model

For range of temperature variables, two-week lag of range of temperature was the best predictor between absolute range of temperature and monthly lag of range of temperature when added to the base model individually. When examining the performance of animals with the thermal environment, the magnitude and duration of thermal stress are important. Other studies examining the effect of cold weather where animals were maintained at constant temperature in psychrometric chambers have been criticized because experimental animals were not subjected to temperature fluctuations normally experienced during wintering (Macdonald and Bell, 1958). Macdonald and Bell (1958) concluded that just because there is little change in homeothermy because of temperature fluctuation does not mean that thermal stress in low temperatures must also be small. In fact, it could be that despite all the physiological adaptations made by the animals in their study, there were still observable changes since they were not able to maintain complete homeothermy. In a study by Mears and Groves (1969), using mature, shorn wethers exposed to lowered temperatures from 14 to -4 °C. They observed no significant change in metabolic rate or rectal temperature for at least 12 hours. After 12 hours, there was a marked increase in adrenal cortical response. This indicates that fluctuating weather affects the physiology of animals.

3.5.5. Wind Speed Predictors with Base Model

Monthly lag of wind speed was the best predictor variable when added to the base model. Wind speed affects the thermal balance of the animal's body. Cold temperatures and wind speed interact together to affect the effective ambient temperature of an animal, and this is referred to as the wind-chill effect (Ames and Insley, 1975). Long-term housing of animals on pasture or in feedlots in the winter with air temperature of -20°C and air velocity of 5 to 7 m/s can result in frost bite or hypothermia (Ruban et al., 2020). On the other hand, in the summer months, significant air velocity could be beneficial by helping to dissipate excess heat from the animal's body.

When air velocity is increased, Basharat (2020) reported that effective ambient temperature is lowered which produces a wind chill index in hot weather comparable to the wind chill index commonly referred to during cold weather. Basharat (2020) reported that in dairy cows, between 26˚C and 36 ˚C, the rate of rise of rectal temperature was reduced by half with increased air velocity of 1.5 to 3.0 m/s as compared to a mean air velocity of 0.5 m/s. Blair et al. (1996) examined the effects of solar radiation, windspeed and their interaction on metabolic rates in the Verdin, *Auriparus flaviceps*. They reported a 14% increase in basal metabolic rate as wind speed increases from 0.4 to 3.0 m/s in the absence of solar radiation. While exposure to simulated solar radiation significantly reduced metabolic heat production at all wind speeds measured except at 3.0 m/s. Convective cooling is altered by wind speed which affects the ability of the animal to maintain thermal balance (Mader 2003). Mader (2003) reported that cold stress in the winter can be exacerbated by evaporative cooling. Silanikove (2000) explained convection cooling as a process in which cooler air comes in contact with a warmer body thereby resulting in dissipation of heat that is carried away with the movement of air.

3.5.6. Dew Point Predictors with Base Model

Two-week lag of dew point was the best predictor when added to the base model. Dew point was used in this study in place of relative humidity because previous authors (Ahlberg et al., 2018) have shown that dew point could be used in place of relative humidity. Dew point could be better in predicting DMI because there is a strong relationship between temperature and humidity and temperature at which relative humidity was measured is not usually known (Walter et al., 2000). Eigenberg et al. (2005) examined the physiological response of feedlot cattle with shade or no shade access. Eigenberg et al. (2005) reported that for temperature above 27˚C, a higher dew point temperature results in higher respiration rates in the animals when compared to the lower dew point temperature conditions.

3.5.7. Significant and Non-Significant Variables

The addition and removal of the significant ($P < 0.05$) main effects to the base model in the second step of stepwise regression is shown in Table 3.5. Table 3.6 shows the significant ($P < 0.05$) main effects and all the possible interactions between the main effect variables. The non-significant ($P > 0.05$) variables that were removed from Table 3.6 are shown in table 3.7. These are the variables that did not improve fit of the model, at various steps of the backward stepwise regression process. Table 3.8 shows the significant ($P < 0.005$) variables in the final model. There were interactions between various weather variables. From the weather variables, two-week lag of range of temperature was the greatest contributor to the base model. This suggests that wide variation in temperature affects DMI since cattle maintain homeostasis by adjusting their metabolic heat production as a response to the change in environmental temperature (NRC, 1981).

Table 3.5. Addition and removal of main effects in a stepwise fashion

Variable[1]	P-value	Process[2]	Criterion	
			AIC[3]	BIC[4]
Base model			45,151	45,160
Two-week lag of ambient temperature[5]	0.0001	A	45,017	45,038
Monthly lag of solar radiation	0.3012	NR	45,018	45,040
Two-week lag of range of temperature[5]	0.0001	A	44,944	44,965
Monthly lag of wind speed[5]	0.0001	A	44,892	44,914
Absolute dew point[5]	0.0001	A	44,872	44,895
Monthly lag of solar radiation	0.0248	NR	44,870	44,892
Absolute solar radiation	0.0698	NR	44,871	44,894
Two-week lag of solar radiation[5]	0.0001	A	44,815	44,838

[1] Variable with 13,895 observations,
[2]A = Addition of variable. NR on the same row variables were not retained. Units are ˚C for ambient temperature, range of temperature and dew point, m/s for wind speed and W/m^2 for solar radiation.
[3]AIC = Akaike information criterion
[4]BIC = Bayesian information criterion
[5]Main effect variables that qualified for the next step of interactions.

Table 3.6. Significant main effects and all possible interactions between the variables

Variable[1]	**F-value**	**P-value**
Base model		
Week of the year	31.13	0.0001
BW, kg		
Linear	389.01	0.0001
Quadratic	155.5	0.0001
NEm, Mcal/kg		
Linear	15.65	0.0001
Quadratic	30.62	0.0001
Two-week lag of ambient temperature	64.45	0.0001
Two-week lag of range of temperature	8.95	0.0028
Monthly lag of wind speed	1.17	0.2801
Absolute dew point	1.09	0.2964
Two-week lag of solar radiation	17.34	0.0001
Two-week lag of ambient temperature × Two-week lag of range of temperature	42.04	0.0001
Two-week lag of ambient temperature × Monthly lag of wind speed	28.95	0.0001
Two-week lag of ambient temperature × Absolute dew point	3.08	0.0791
Two-week lag of ambient temperature × Two-week lag of solar radiation	32.35	0.0001
Two-week lag of range of temperature × Monthly lag of wind speed	4.00	0.0455
Two-week lag of range of temperature × Absolute dew point	1.50	0.2202
Two-week lag of range of temperature × Two-week lag of solar radiation	2.91	0.0879
Monthly lag of wind speed × Absolute dew point	1.29	0.2555
Monthly lag of wind speed × Two-week lag of solar radiation	6.00	0.0144
Absolute dew point ×Two-week lag of solar radiation	1.25	0.2626

[1] Variable with 13,895 observations. Units are ˚C for ambient temperature, range of temperature and dew point, m/s for wind speed and W/m^2 for solar radiation. AIC = Akaike information criterion (44,734), BIC = Bayesian information criterion (44,759).

Table 3.7. Summary of variables removed from the model in the second stage. Cut off points used were P-value = 0.02 and F-value = 5.0

Variable[1]	F-value	P-value	Elimination step	Criteria	
				AIC[2]	BIC[3]
Base model					
Absolute dew point	1.09	0.2964	1	44,733	44,758
Monthly lag of wind speed × Absolute dew point	0.22	0.6406	2	44,731	44,756
Absolute dew point ×Two-week lag of solar radiation	1.00	0.3180	3	44,730	44,755
Monthly lag of wind speed	4.55	0.033	4	44,732	44,756
Two-week lag of range of temperature × Monthly lag of wind speed	1.09	0.2962	5	44,731	44,755
Two-week lag of range of temperature × Two-week lag of solar radiation	2.81	0.0934	6	44,731	44,755

1 Variable with 13,895 observations. Units are ˚C for ambient temperature, range of temperature and dew point, m/s for wind speed and W/m^2 for solar radiation.
[2]AIC = Akaike information criterion
[3]BIC = Bayesian information criterion

Table 3.8. Final model with significant variables with REML estimation

Variable[1]	Estimates	SE[2]	F-value	P-value
Intercept	-5.56×10^{0}	1.25×10^{0}		0.0016
Base model				
Week of the year			32.56	0.0001
BW, kg				
Linear	4.48×10^{-2}	2.26×10^{-3}	391.20	0.0001
Quadratic	-3.00×10^{-5}	2.26×10^{-6}	155.01	0.0001
Dietary NEm, Mcal/kg				
Linear	3.84×10^{0}	9.66×10^{-1}	15.77	0.0001
Quadratic	-1.35×10^{0}	2.43×10^{-1}	30.82	0.0001
Two-week lag of ambient temperature,	-1.92×10^{-1}	1.96×10^{-2}	95.57	0.0001
Two-week lag of range of temperature	-1.09×10^{-1}	1.04×10^{-2}	110.07	0.0001
Two-week lag of solar radiation	1.46×10^{-2}	1.51×10^{-3}	94.61	0.0001
Two-week lag of ambient temperature × Two-week lag of range of temperature	7.14×10^{-3}	1.09×10^{-3}	42.94	0.0001
Two-week lag of ambient temperature × Monthly lag of wind speed	3.24×10^{-2}	4.49×10^{-3}	52.00	0.0001
Two-week lag of ambient temperature × Absolute dew point	-7.80×10^{-4}	2.76×10^{-4}	8.01	0.0047
Two-week lag of ambient temperature × Two-week lag of solar radiation	-3.40×10^{-4}	6.10×10^{-5}	31.98	0.0001
Two-week lag of range of temperature × Absolute dew point	-2.10×10^{-3}	2.90×10^{-4}	52.29	0.0001
Monthly lag of wind speed × Two-week lag of solar radiation	-1.63×10^{-3}	3.32×10^{-4}	24.09	0.0001

1 Variable with 13895 observations. Units are ˚C for ambient temperature, range of temperature and dew point, m/s for wind speed and W/m^2 for solar radiation.
[2]SE= Standard error AIC = Akaike information criterion (44,912), BIC = Bayesian information criterion (44,920)

3.5.8. How Weather Variables Interacted to Affect DMI

The interaction between ambient temperature and range of temperature is shown in Figure 3.1. DMI decreases as temperature gets colder and fluctuation increases while DMI increases with increasing warmer temperatures and higher fluctuations in temperature. Macdonald and Bell (1958) studied the effect of low fluctuating temperature on rectal temperature, heart rate and respiratory rate in lactating Holstein cows. They observed small changes in the parameters they measured (rectal temperature, heart rate and respiration rate) and concluded that the lactating cattle were quite comfortable at temperatures near -17 ˚C in their study and as reported in other studies (Kibler and Brody, 1950; Worstell and Brody 1953). The reason attributed to the small changes observed are cited compensatory mechanisms which enhances tolerance to cold. These mechanisms may be water removal from the circulatory system, peripheral vasoconstriction, increasing surface area by huddling, decreasing respiration rate, increasing the amount of protective hair, developing extensive subcutaneous adipose tissue, and increasing appetite and metabolism through endocrinological stimulation.

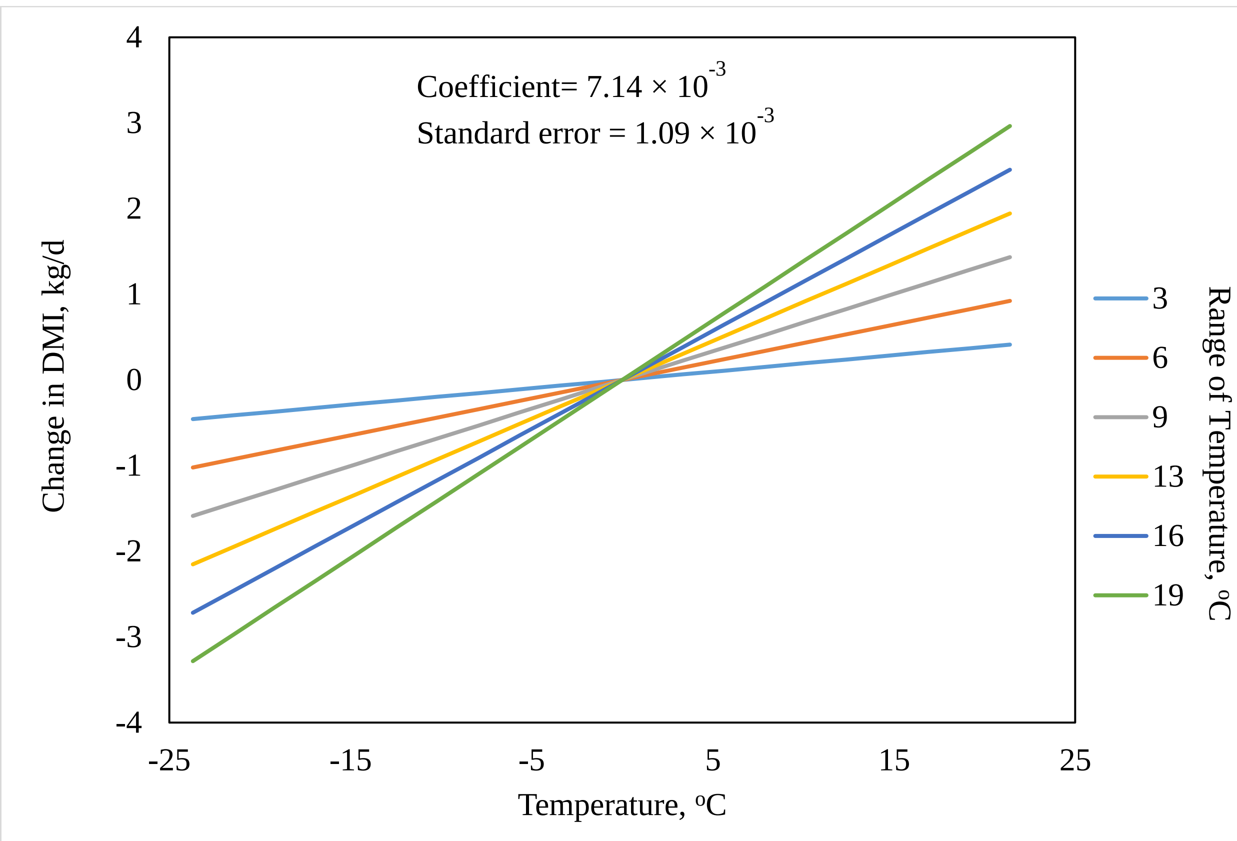

Figure 3.1. Interaction between ambient temperature and range of temperature

The interaction between temperature and wind speed is shown in Figure 3.2. It was observed that with decreasing temperature and increasing wind speed, DMI decreases. This shows how wind speed exacerbates the effect of cold temperatures in cattle which results to extreme cold stress and therefore decreased DMI. This is supported by the reports of NASEM (2016) about how adverse environmental factors like wind accentuates the effect of ambient temperature which then alters DMI.

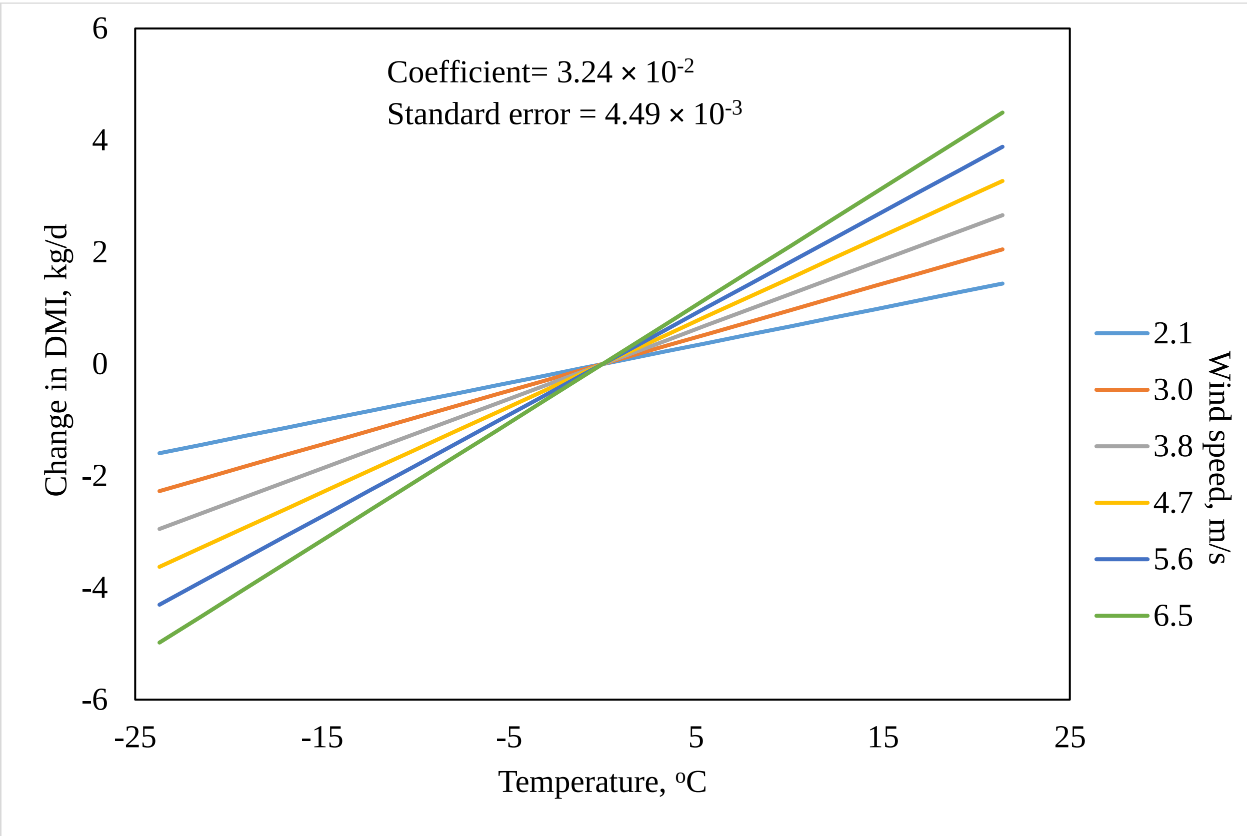

Figure 3.2. Interaction between ambient temperature and wind speed

The interaction between ambient temperature and dew point is shown in Figure 3.3. There is a strong association between the moisture content of the air and temperature, it has been reported that it is much worse to be hot and humid than either been hot or just humid (Walter et al., 2000). This is similar to what was observed in our model. This explains the effect experienced when high temperature and moisture in the air causes more stress in an animal which indirectly results in changes in metabolism and subsequently changes in DMI.

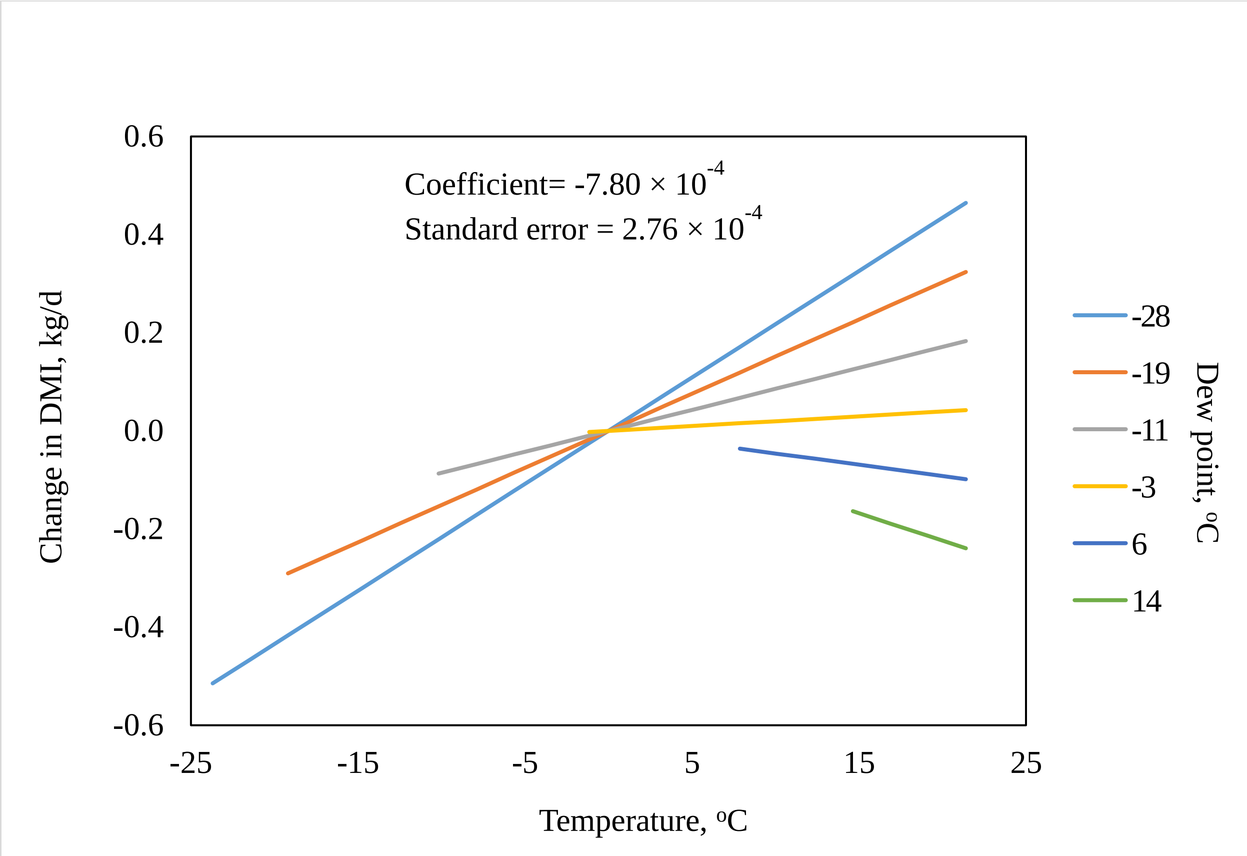

Figure 3.3. Interaction between ambient temperature and dew point

The interaction between ambient temperature and solar radiation is shown in Figure 3.4. It shows that in cold temperature, and high solar radiation, DMI increases. On the other hand, as temperature increases while solar radiation decreases, DMI decreased. There is a dearth of information on the relationship between ambient temperature and solar radiation in cold weather conditions. Few studies that have examined the influence of solar radiation and temperature in livestock were conducted in warm to hot environments (Mader et al., 2006; Melton; 2018). A classic study by Olson (1938) who examined the effect of solar radiation in dairy cattle in a temperate environment reported that cattle left under outside under cold and direct solar radiation require more energy compared with cattle that are not exposed to direct cold and solar radiation. Olson (1938) attributed the difference between the two treatment groups to the energy demand when animals are exposed to harsh weather conditions. This is similar to what was observed in this study where DMI is being affected by the interaction between ambient temperature and solar radiation. This interaction corroborates the report of Mader et al (2010) that reported that a linear relationship exists between ambient temperature and solar radiation.

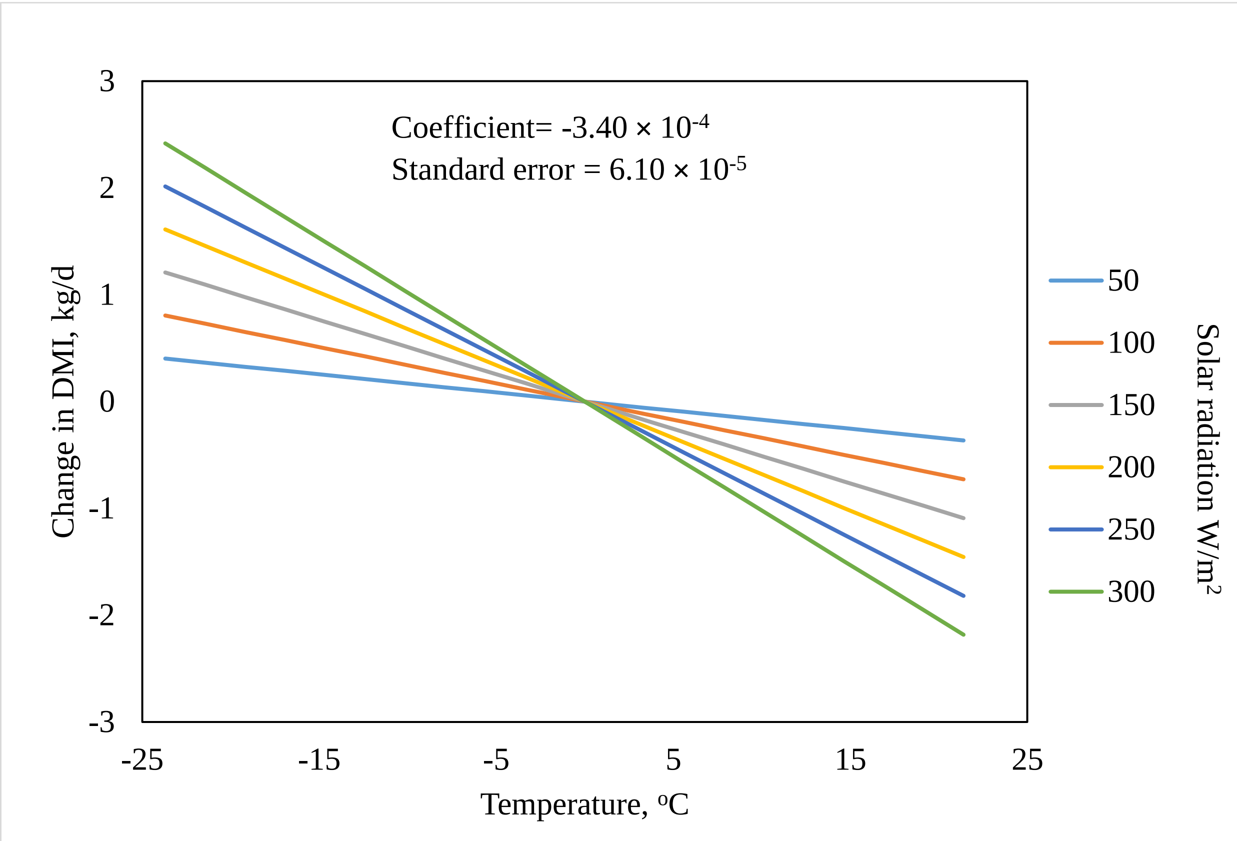

Figure 3.4. Interaction between ambient temperature and solar radiation

The interaction between range of temperature and dew point is shown in Figure 3.5. DMI decreases with increasing range of temperature and increasing dew point while DMI increases with increasing range of temperature and decreasing dew point. Fluctuating temperature and amount of moisture in the air could have a significant impact on animals DMI because cattle rely on evaporative cooling as a mean of energy loss (Blaxter, 1962). This process is affected negatively when the dew point in the air is high because of a reduced moisture gradient between the respiratory surface and the air. Stressed animals with reduced rate of evaporative cooling will have to adjust their metabolism to maintain homeothermy which could result in the observed change in DMI. Cattle in the temperate region have been reported to be more sensitive to increasing changes in temperatures and high dewpoint. This causes decrease in DMI which suggests that they may be more sensitive to high ambient heat than is recognized currently (Hill and Wall, 2017).

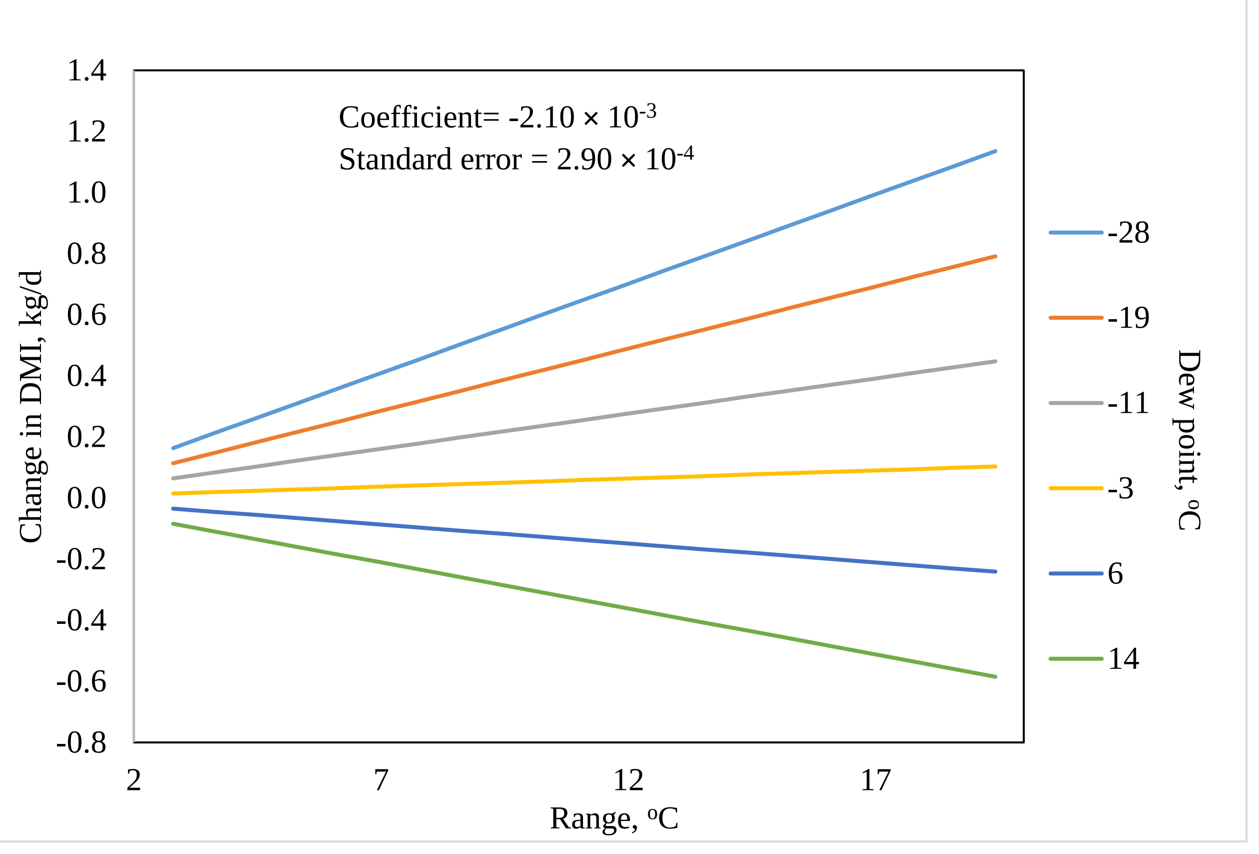

Figure 3.5. Interaction between range of temperature and dew point

Wind speed and solar radiation interacted which decreased DMI. (Figure 3.6). DMI decreased with increasing solar radiation and wind speed. This could be the effect of the radiant heat of the sun that is absorbed by the cattle body which increases its body core temperature especially in dark hided animals which are the major type of animals used in this study (Mader et al., 2006). We presume on humid days, with hot solar radiation and high winds, this increases the heat stress experienced by the animal which then decreases DMI intake. Humidity and heat as explained earlier makes it feel hotter than just humidity or heat alone. Wind speed could also exacerbate this situation. On the other hand, if it is not humid, and it is hot with high wind speed, it is expected that the wind should enhance the rate of evaporative cooling thereby ameliorating the heat stress experienced by the cattle.

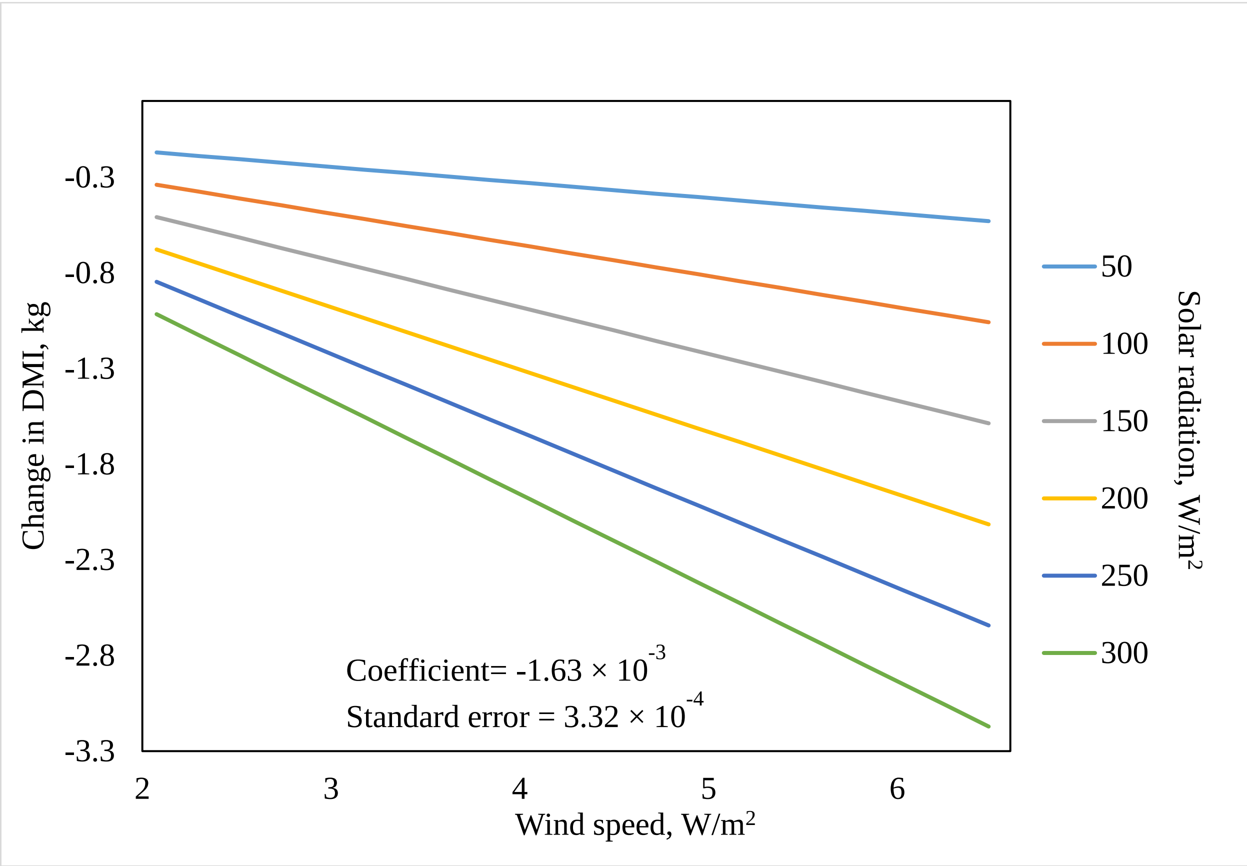

Figure 3.6. Interaction between wind speed and solar radiation

3.6. Conclusion

In this study, we were able to show some relationships between weather variables and how they influence DMI in the Northern Great Plains of North America. Ambient temperature interacted with range of temperature, wind speed, dew point and solar radiation. Other interactions between weather variables were the interaction between range of temperature and dew point, as well as wind speed and solar radiation. This indicates that weather variables interact together and should be considered when creating DMI prediction models for beef cattle in the Northern Great Plains. This will help in a better understanding of the factors that regulates intake which warrants the need for empirical models as highlighted by Fisher (2002).

3.7. Implications

This study has helped in our understanding of weather variables that have an influence on DMI and will facilitate improvement in the accuracy of current DMI models. More accurate DMI predictions will assist producers in planning and making better decisions regarding the management of their feed resources. At the same time, scientist and producers now have a better knowledge of how each weather variable modeled interacts and how they have an impact on DMI.

3.8. Literature Cited

Agricultural Research Council. 1980. The Nutrient requirements of Ruminant Livestock. Agricultural Research Council. The Gresham Press, London.

Ahlberg, C. M., K. Allwardt, A. Broocks, K. Bruno, L. McPhillips, A. Taylor, C. R. Krehbiel, M. S. Calvo-Lorenzo, C. J. Richards, S. E. Place. 2018. Environmental effects on water intake and water intake prediction in growing beef cattle. J. Anim. Sci. 96:4368–4384. DOI:10.1093/jas/sky267

Ames, D. R., and L. W Insley. 1975. Wind-chill effect for cattle and sheep. J. Anim. Sci. 40:1 DOI: 10.2527/jas1975.401161x

Anele, U. Y., E. M. Domby, and M. L. Galyean. 2014. Predicting dry matter intake in growing and finishing beef cattle: Evaluation of current methods and equation development. J. Anim. Sci. 92:2660-2667 DOI: 10.2527/jas.2014-7557

Appuhamy, J. A. D., L. E. Moraes, C. Wagner-Riddle, D. P. Casper, J. France, and E. Kebreab. 2014. Development of mathematical models to predict volume and nutrient composition of fresh manure from lactating Holstein cows. Anim. Prod. Sci., 54:1927-1938 DOI: 10.1071/AN14533

Basharat, S. 2020. Effects of Air velocity of dairy cow. Retrieved from https://www.linkedin.com/pulse/effects-air-velocity-dairy-cow-sohail-basharat?trk=public_profile_article_view on June 3rd, 2021.

Blair, O. W., and E. G. Walsberg. 1996. Thermal effects of radiation and wind on a small bird and implications for microsite selection. Ecology, 77:2228-2236 DOI: https://doi.org/10.2307/2265716

Blaxter, K. L. 1962. The Energy Metabolism of Ruminants, Hutchinson's Scientific and Technical Publications, London, UK.

Bourke, C. 2003. Evidence that enforced sunlight exposure can cause hyperthermia in cattle ingesting low levels of ergot of rye (Claviceps purpurea), when air temperature and humidity conditions are only moderate. Austr. Vet. J., 81:553-55 DOI: https://doi.org/10.1111/j.1751-0813.2003.tb12886.x

Dikmen, S., and P. Hansen. 2009. Is the temperature-humidity index the best indicator of heat stress in lactating dairy cows in a subtropical environment? J. Dairy Sci., 92:109-116 DOI: https://doi.org/10.3168/jds.2008-1370

Eigenberg, R. A., T. M Brown-Brandl, J. A. Nienaber and G. L. Hahn. 2005. Dynamic response indicator of heat stress in shaded and non-shaded feedlot cattle, part 2: Predictive relationships. Biosystems Engineering. 91:111–118 DOI:10.1016/j.biosystemseng.2005.02.001

Fox, D. G., L. O. Tedeshi, T. P Tylutki, J. B Russell, M. E. van Amburgh, L. E Chase, A. N. Pell, and T. R. Overton. 2004. The Cornell Net Carbohydrate and Protein System model for evaluating her nutrition and nutrition excretion. Anim. Feed Sci. Tech. 122:29-78 DOI: https://doi.org/10.1016/j.anifeedsci.2003.10.006

Graunke, K. L., T. Schuster, and L. M. Lidfors. 2011. Influence of weather on the behaviour of outdoor-wintered beef cattle in Scandinavia. Livest. Sci. 136:247–255. DOI: 10.3390/ani11051261

Hahn G. L. (1999) Dynamic responses of cattle to thermal heat loads. J. Anim. Sci. 77 (Suppl. 2):10-20 DOI: 10.2527/1997.77suppl_210x

Hammami, H., J. Bormann, N. M'hamdi, H. Montaldo, and N. Gengler. 2013. Evaluation of heat stress effects on production traits and somatic cell score of Holsteins in a temperate environment. J. Dairy Sci. 96:1844–1855. DOI: https://doi.org/10.3168/jds.2012-5947

Hill, D. L., and Wall E. 2017. Weather influences feed intake and feed efficiency in a temperate climate. J. Dairy Sci. 100:2240-2257 DOI: https://doi.org/10.3168/jds.2016-11047

Hill, D., and E. Wall. 2015. Dairy cattle in a temperate climate: The effects of weather on milk yield and composition depend on management. Animal 9:138–149. DOI: https://doi.org/10.1017/S1751731114002456

Kibler, H. H. and S. Brody. 1950. Environmental physiology with special reference to domestic animals. XI. Effects of temperature 50 to 105°F and 50° to 9° F on heat production and cardiorespiratory activities in Brahman, Jersey, and Holstein cows. Missouri Expt. Sta. Res. Bull. No. 464.

Lofgreen, G. P., and W. N. Garett. 1968. A system for expressing net energy requirements and feed values for growing and finishing beef cattle. J. Anim. Sci. 27:793-806

Mader, T. L. 2003. Environmental stress in confined beef cattle. J. Anim. Sci. 81(E. Suppl.): E110–E119. DOI: https://doi-org.eres.qnl.qa/10.2527/2003.8114_suppl_2E110x

Mader, T. L., L. J. Johnson, and J. B. Gaughan. 2010. A comprehensive index for assessing environmental stress in animals. J. Anim. Sci. 88:2153-2165. DOI: 10.2527/jas.2009-2586

Mader, T. L., M. S. Davis, and T. Brown-Brandl. 2006. Environmental factors influencing heat stress in feedlot cattle. J. Anim. Sci. 84:712–719. DOI: 10.2527/2006.843712x

McDonald, M. A., and J. M. Bell. 1958. Effects of low, fluctuating air temperatures on farm animals. 1. Influence of ambient air temperature on the respiration rate, heart rate and rectal temperature of lactating holstein friesian cows. Can. J. Anim. Sci. 38:10–22. DOI: https://doi.org/10.4141/CJAS58-022

Mears, G. J. and T. D. D. Groves. 1969. Some physiological responses of sheep to short term cold exposure. Canadian J. Anim. Sci. 49:389. DOI: https://doi.org/10.4141/cjas69-051

Melton, B. M., T. Winders, B. M. Boyd, C. N. Macken, A. K. Watson, J. C. MacDonald, and G. E. Erickson. 2018. Impact of Shade on Performance, Body Temperature, and Heat Stress of Finishing Cattle in Eastern Nebraska. 10th International Livestock Environment Symposium (ILES X) DOI: https://doi.org/10.13031/iles.18-098

Montanholi, Y. R., K. C. Swanson, R. Palme, F. S. Schenkel, B. W. McBride, D. Lu, and S. P. Miller. 2010. Assessing feed efficiency in beef steers through feeding behavior, infrared thermography and glucocorticoids. Animal 4:692-701. DOI: 10.1017/S1751731109991522

Mount, L. E. 1979. Adaptation to Thermal Environment. Man and His Productive Animals. Univ. Park Press, Baltimore, MD.

National Academies of Science, Engineering, and Medicine. 2016. Nutrient requirements of beef cattle, 8th Rev. Ed. Washington DC: The National Academies.

NRC. 1981. Effect of Environment on Nutrient requirements of Domestic Animals. National Academy Press, Washington, DC

NRC. 1996. Nutrients Requirement of Beef cattle. (7th Ed.). Nutrient requirement of domestic animals. National Academy Press, Washington, D.C

NRC. 2001. Nutrients Requirement of Dairy Cattle. (7th Ed.). Nutrient requirement of domestic animals. National Academy Press, Washington, D.C

North Dakota Agricultural weather station (NDAWN). 2021. Available at https://ndawn.ndsu.nodak.edu/

Olson, T. M. 1938. Effect of sunlight on the growth, production, and reproduction of dairy cattle. Bulletins. Paper 319. http://openprairie.sdstate.edu/agexperimentsta_bulletins/319

Renaudeau, D., A Collin, S. Yahav, V de Basilio, J Gourdine, and R Collier. 2012. Adaptation to hot climate and strategies to alleviate heat stress in livestock production. Animal 6:707-728 DOI: https://doi.org/10.1017/s1751731111002448

Ruban, S., Borshch, O.O., Borshch, O.V., Orischuk, O., Balatskiy, Y., Fedorchenko, M., Kachan, A., and M. Zlochevskiy. 2020. The impact of high temperatures on respiration rate, breathing condition and productivity of dairy cows in different production systems. Animal Science Papers and Reports 38:61–72. DOI: 20203167447

SAS User's Guide: Statistics. 2004. SAS Institute Inc., Cary, NC.

Silanikove, N. 2000: Effects of heat stress on the welfare of extensively managed domestic ruminants. Livestock Prod. Sci. 67:1-18. DOI: https://doi.org/10.1016/S0301-6226(00)00162-7

Swanson, K. C., A. Islas, Z. E. Carlson, R. S. Goulart, T. C. Gilbery, and M. L. Bauer. 2014. Influence of dry-rolled corn processing and increasing dried corn distillers grains plus solubles inclusion for finishing cattle on growth performance and feeding behavior. J. Anim. Sci. 92:2531-2537. DOI: 10.2527/jas.2013-7547

Walter, I. A., R. G. Allen, R. Elliott, B. Mecham, M. E. Jensen, D. Itenfisu, T. A. Howell, R. Snyder, P. Brown, S. Echings, T. Spofford, M. Hattendorf, R. H. Cuenca, J. L. Wright, and D. Martin. 2000. ASCE standardized reference evapotranspiration equation. In: R. G. Evens, B. L. Benham, T. P. Trooien, editors, Proc. Natl. Irrig. Symp. ASAE, Phoenix, AZ. pp. 209–215.

Worstell, D M and S. Brody. 1953 Environmental physiology and shelter engineering with special reference to domestic animals. Comparative physiological reactions of European and Indian cattle to changing temperature. Missouri Expt. Sta. Res. Bull. 515. 1. URL: https://hdl.handle.net/10355/63187

Zinn, R. A., and Y. Shen. 1998. An evaluation of ruminally degradable intake protein and metabolizable amino acid requirements of feedlot calves. J. Anim. Sci. 76:1280-1289 DOI: 10.2527/1998.7651280x

CHAPTER 4. THE INFLUENCE OF WEATHER VARIABLES ON AVERAGE DAILY GAIN OF BEEF STEERS

4.1. Abstract

Average daily gain is one of the most important measures producers utilize to measure productivity of beef cattle. The objective was to examine how weather variables influence ADG. Data from 790 beef steers collected through an Insentec feeding system were utilized for this study. Daily data was condensed into weekly averages (n = 13,739 steer-weeks). The variables considered were ADG (-3.0 to 4.86 kg/d), DMI (2.50 to 21.77kg/d), BW (197.3 to 796.1 kg), dietary energy density (NEm; 1.2 to 2.5 Mcal/kg), average ambient temperature (-23.7 to 21.4 °C), range of temperature (2.8 to 19.4 °C), dew point (-27.8 to 14.3 °C), wind speed (2.08 to 6.49 km/h), solar radiation (30.8 to 297.1 W/m^2), and two-week lag (average of previous two week's values) and monthly lag (average of previous four week's values) of each weather variable. Relationship between weather variables were considered while developing the model, including controlling for confounding variables. Residuals of ADG generated after fitting week of year as a fixed effect and experiment as a random effect were used in scatter plots with explanatory variables to identify if non-linear relationships existed. The MIXED procedure of SAS with Toeplitz variance-covariance structure was used to determine the final model of ADG, while accounting for the effects of DMI, BW, dietary NEm and weather variables in the model. Body weight and dietary energy density had linear relationships with ADG. Absolute dew point, two-week lag of ambient temperature and monthly lag of wind speed had positive associations with ADG. DMI, BW, NEm and range of temperature had a positive association with ADG. Monthly lag of solar radiation interacted with monthly lag of range of temperature, absolute dew point, two-week lag of ambient temperature and monthly lag of wind speed and accounted for variation

in ADG. Other interactions were monthly lag of range of temperature interacting with dew point and wind speed. Absolute dew point and two-week lag of ambient temperature also interacted all significantly (P = 0.0001) affecting ADG. These data indicate that weather variables and their interactions influence ADG and should be considered in ADG prediction equations.

4.2. Introduction

The overall aim of any beef cattle producer is to have a profitable enterprise and for this to be achieved, the producer will need a system that will improve feed efficiency, minimize costs, and increase profits (Archer et al., 1998; Miller et al., 2001; Basarab et al., 2007). Feed is the major cost of beef production and production system efficiency depends on the feed input and production output (Archer et al., 1998). One of the most important measures that beef cattle producers utilize is average daily gain (ADG). Average daily gain (kg/d) is the amount of gain (kg) accumulated per unit of feed, termed gain to feed (G:F) daily. There are many factors that affect ADG which could either be grouped as genetic, environmental or their interaction. Environmental factors that could affect ADG includes nutrition, management, disease, and weather factors. The weather factors could include ambient temperature, wind speed, solar radiation, and dew point. In extreme weather conditions, the net energy requirement of animals is affected (NRC, 1981). Cold or heat stress, below or above the lower and upper critical temperature of animals, triggers physiological responses which result in behavioral changes in the animal. In cold conditions, the animal maintains homeostasis by peripheral vasoconstriction to help in reducing energy loss to the environment while on the other hand, in heat stressed animals, the mechanism is peripheral vasodilation where more heat is carried by the blood to the skin and therefore lost to the environment. In any of the conditions above, the performance of the animal could be affected because the maintenance of homeostasis is associated with hormonal and metabolic changes. These metabolic changes could directly have an influence on the performance of the animal since the basal metabolism of the animal is influenced. Basal metabolism is an outcome of chemical change which occurs in animal cells in their fasting and resting state utilizing just adequate energy to maintain vital cellular activity, respiration, and circulation (NRC, 1981). Weather variables could have an impact on basal metabolism, which in turn determines the net energy requirement of the animal. Net energy requirement of the animal is used for formulating diets for cattle and are divided into net energy for maintenance (NEm) and net energy for gain (NEg). Energy for maintenance must be met first before the animal can use the rest for gain (NEg). Since the thermal environment influences NEm, it indirectly influences NEg, which will determine the ADG of the animal. The objective of this study is to examine the influence of weather variable on ADG of beef steers.

4.3. Materials and Methods

4.3.1. Data Collection

Data used for this experiment were collected from the Beef Cattle Research Complex of North Dakota State University, Fargo, North Dakota located at latitude 46.9027853 degrees North and longitude -96.8418183 degrees West. An Insentec feeding system (RIC feeding system; Hokofarm Group, Marknesse, The Netherlands), which records the amount of feed intake, number of visits, time of visit and meals for each animal, was used for the data collection. The data used were from 10 experiments that were conducted between 2011 and 2017 (Table 4.1).

Table 4.1. Experiments used in this study

Year (week of the year)		n[1] of steers	n of steer-week observations	Breed[2]	Publication
Start	End				
2011 (wk. 45)	2012 (wk. 4)	67	804	AN, SM, and SH	Islas et al., 2014
2012 (wk. 46)	2013 (wk. 5)	94	1120	AN, SM, and SH	Prezotto et al., 2017
2012 (wk. 10)	2012 (wk. 22)	63	819	AN, SM, and SH	Swanson et al., 2014
2013 (wk. 6)	2013 (wk. 22)	66	1098	AN, SM, and SH	Swanson, et al., 2017a
2013 (wk. 38)	2014 (wk. 5)	113	2260	AN-crossbred	Swanson et al., 2018
2014 (wk. 11)	2014 (wk. 22)	44	527	AN, SM, and SH	Swanson et al., 2017a
2014 (wk. 4)	2014 (wk. 22)	81	1339	AN, SM, and SH	Rodenhuis et al., 2017
2015 (wk. 51)	2016 (wk. 18)	61	1211	AN, SM, and SH	Knutson et al., 2020
2016 (wk. 45)	2017 (wk. 20)	134	3432	AN, SM, and SH	Sitorski et al., 2019
2017 (wk. 46)	2018 (wk. 11)	67	1285	AN and SM	Trotta et al., 2019

[1]n=number
[2]AN = Angus, SM = Simmental, SH = Shorthorn

4.3.2. Weather Data

Data for weather variables were obtained from the North Dakota Agricultural Weather Network (NDAWN) station for each experiment period included in this study. Each NDAWN station is assumed to adequately represent all weather conditions, except rainfall, in a 32 km radius (NDAWN, 2021). The NDAWN station, which is 2.33 km from the BCRC, provides five-minute averages, hourly averages, daily, monthly, and yearly summaries for each supported weather variable (NDAWN, 2021). For this study, daily summaries of each weather variable were used for each experiment period included.

Weather variables modeled for this study included:

- Ambient temperature: the air temperature of the surrounding environment (˚C)
- Absolute range in temperature: the difference between absolute minimum and absolute maximum temperature
- Dew point: the temperature at which water vapor in the air begins condensing to form liquid. The dew point temperature is calculated from the air temperature and

relative humidity. Dew point temperature units are Fahrenheit or Celsius (NDAWN, 2021).

- Wind speed: average of all measured wind speeds during the hour for a period of 24 hours). Wind speed is measured every 5 seconds 10 meters above the soil surface with an anemometer (NDAWN, 2021).
- Solar radiation: total of all hourly totals of incident solar radiation energy for a 24-hour period from midnight to midnight (W/m2) (NDAWN, 2021). Total incident solar radiation flux density is measured in Watts/m^2 at approximately 2 m above the soil surface with a pyranometer
- The two-week lag and monthly lag of each weather variable was also considered. Two-week lag is the average of the previous two week's weather variable while monthly lag is the average of the previous month's weather variable in question.

4.3.3. Non-Weather Variables

The non-weather variables considered for this experiment include weekly average daily gain (ADG), weekly average daily dry matter intake (DMI), weekly average body weight (BW), dietary net energy of maintenance (NEm), experiment, and the week of the year. Week of the year ranged from week 1 to 22 and week 30 to 52. In this study, only 1 experiment had observations for weeks 23 to 29 which will result in inadequate sample and cause scaling issues if they were included in models.

4.3.4. Data Management

Weekly average of ADG was calculated by dividing the difference in weekly BW by 7. The daily feed intake data was averaged into weekly averages to reduce the day-to-day fluctuation. The weekly dry matter analysis of the diet fed from each experiment was matched with the weekly feed intake to calculate the actual DMI consumed by each animal. Weekly BW for each animal was calculated from the monthly BW data values by using simple linear regression. Values for daily ambient temperature and solar radiation were converted into weekly averages. Dietary energy density (NEm,) was calculated by using the equation of Lofgreen and Garrett (1968) and Zinn and Chen (1998) using initial BW, final BW, average daily gain (ADG) and average DMI. The descriptive statistics of the variables used in this study is shown in Table 4.2.

Table 4.2. Descriptive statistics of the variables used for this study

Variable[1]	Mean	Minimum	Maximum	SD[2]	SE[3]
ADG, kg/d	1.56	-3.04	4.86	0.77	0.006
BW, kg	474.45	197.31	796.06	99.11	0.84
DMI, kg/d	10.69	2.50	21.77	2.74	0.02
NEm, Mcal/kg	2.01	1.19	2.52	0.24	0.00
Ambient temperature, ˚C					
No lag	-2.01	-23.73	21.40	10.45	0.09
Two-week lag	-2.18	-20.73	23.56	9.58	0.08
Monthly lag	-2.20	-17.95	22.74	9.05	0.08
Range of temperature, ˚C					
No lag	10.46	2.79	19.43	2.66	0.02
Two-week lag	10.28	4.57	15.80	2.24	0.02
Monthly lag	10.18	5.94	15.02	1.76	0.01
Wind speed, m/s					
No lag	3.84	2.08	6.49	0.71	0.01
Two-week lag	3.85	2.34	4.96	0.52	0.00
Monthly lag	3.83	2.79	4.64	0.40	0.00
Solar radiation, W/m^2					
No lag	112.81	30.81	297.12	64.00	0.55
Two-week lag	107.30	34.56	271.98	58.57	0.50
Monthly lag	104.47	43.66	256.57	54.34	0.46
Dew point, ˚C					
No lag	-7.00	-27.84	14.34	8.92	0.08
Two-week lag	-6.97	-24.59	16.96	8.15	0.07
Monthly lag	-6.89	-21.61	14.94	7.67	0.07

[1] Variable with 13,739 observations,
[2]SD = Standard error
[3]SE = Standard deviation.

4.3.5. Statistical Analysis

Data were analyzed as a repeated measures design using the MIXED procedures of (SAS Inst., Cary, NC) and within-individual relationship was accounted for using the Toeplitz covariance structure. Week of the year was used as fixed effect and experiment was included as a random effect to output the residuals. Correlation among weather variables was checked using the PROC CORR statement of SAS. Linear and quadratic effects of all the weather variables modeled were tested.

The model for fitting residuals, the base model and the final model were analyzed using the restricted maximum likelihood estimation method (REML), while the maximum likelihood (ML) was used in each step of the stepwise addition or removal of variables. Akaike information criterion (AIC) and Bayesian information criterion (BIC) values were used to assess model fit each time a variable was added to the model in a forward stepwise fashion. The parameter estimates were outputted using the solution statement. The full model was refitted using REML to obtain less biased estimates. For all the models, components with ($P < 0.05$), F-values, and their respective AIC and BIC values are reported.

4.4. Results and Discussion

4.4.1. Base Model

The variables included in the base model (Table 4.3) are week of the year (fixed effect), experiment (random effect), linear effect of BW, and linear effect of NEm. The quadratic effect of BW and NEm did not improve the model fit so it was not included in the base model. The AIC and BIC values of the base model were 18,609 and 18,618, respectively.

Table 4.3. Variables in the base model to predict ADG

Variable[1]	Estimates	SE[1]	F-value	P-value
Week of the year	-	-	29.89	0.0001
DMI, kg/d	0.01059	0.002849	13.80	0.0002
BW, kg	0.002985	0.000175	292.04	0.0001
NEm, Mcal/kg	1.0003	0.1221	67.10	0.0001

[1] Variable with 13,739 observations SE = Standard error, AIC = Akaike information criterion (18,609), BIC = Bayesian information criterion (18,618)

4.4.2. Addition of Weather Variables to the Base Model Individually

The significant form of each weather variable when it was added to the base model is shown in Table 4.4. When ambient temperature predictors were added to the base model individually, monthly lag of ambient temperature accounted for the most variation in ADG. When each of the three solar radiation variables were added individually to the base model, monthly lag of solar radiation accounted for the most variation in ADG. For range of temperature variables, monthly lag of range of temperature accounted for the most variation in ADG when added to the base model individually. When the three wind speed variables were added to the base model individually, two-week lag of wind speed accounted for the most variation in ADG. When absolute dew point, two-week lag of dew point and monthly lag of dew point was added to the base model individually, absolute dewpoint accounted for the most variation in ADG.

Table 4.4. AIC, BIC, F and P values of each weather variable considered when added to the base model individually

Variable[1]	F-value	P-value	AIC[2]	BIC[3]
Base model	-	-	18,609	18,618
Ambient temperature				
No lag	56.35	0.0001	18,412	18,434
Two-week lag	45.74	0.0001	18,423	18,444
Monthly lag	65.24	0.0001	18,403	18,424
Solar radiation				
No lag	2.78	0.0954	18,463	18,485
Two-week lag	88.95	0.0001	18,381	18,403
Monthly lag	296.80	0.0001	18,185	18,207
Range of Temperature				
No lag	0.08	0.7819	18,466	18,487
Two-week lag	20.37	0.0001	18,446	18,468
Monthly lag	56.28	0.0001	18,413	18,434
Wind speed				
No lag	2.09	0.1484	18,464	18,485
Two-week lag	20.74	0.0001	18,447	18,468
Monthly lag	10.68	0.0011	18,456	18,477
Dew point				
No lag	54.61	0.0001	18,415	18,436
Two-week lag	20.98	0.0001	18,446	18,467
Monthly lag	34.78	0.0001	18,433	18,454

[1]Variable with 13,739 observations. Units are °C for ambient temperature, range of temperature and dew point, m/s for wind speed and W/m^2 for solar radiation.
[2]AIC = Akaike information criterion.
[3]BIC = Bayesian information criterion.

4.4.3. Significant and Non-Significant Main Effect Weather Variables

Table 4.5 shows the addition and removal of the main effects that were significant ($P < 0.05$) in the first step of the forward stepwise regression when they were added individually. In this second step, weather variables were added to the base model in forward stepwise and either retained or not retained using a P-value ($P<0.005$) and AIC and BIC values. At the end, for weather variables that were not significant, the other forms of that particular weather variable were tested to examine if they would be significant before the variable was eliminated from the model. Table 4.6 shows the significant main effects only. Table 4.7 shows the significant main effects and all possible interactions between the main effects. The non-significant variables that did not improve the model at the various steps of the backward stepwise regression process were removed. Table 4.8 shows the significant variables in the final ADG model.

Table 4.5. Addition and removal of main effects in a stepwise fashion

Variable[1]	P-value	Process[2]	Criterion	
			AIC[3]	BIC[4]
Base model			18,609	18,618
Monthly lag of solar radiation[5]	0.0001	A	18,185	18,207
Monthly lag of ambient temperature	0.4572	NR	18,187	18,208
Monthly lag of range of temperature[5]	0.0001	A	18,174	18,195
Two-week lag of wind speed	0.2204	NR	18,175	18,196
Absolute dew point[5]	0.0001	A	18,157	18,179
Two-week lag of ambient temperature[5]	0.0001	A	18,134	18,156
Absolute ambient temperature	0.0001	NR	18,141	18,163
Absolute wind speed	0.5930	NR	18,159	18,181
Monthly lag of wind speed[5]	0.0001	A	18,080	18,103

[1]Variable with 13,739 observations. Units are °C for ambient temperature, range of temperature and dew point, m/s for wind speed and W/m^2 for solar radiation.
[2]A = Addition of variable. NR on the same row variables were not retained.
[3]AIC = Akaike information criterion
[4]BIC = Bayesian information criterion
[5]Main effect variables that qualified for the next step of interactions.

Table 4.6. Base model and significant main effects

Variable[1]	P-value	Process	Criterion	
			AIC[2]	BIC[3]
Base model			18,632	18,641
Monthly lag of solar radiation	0.0001	A	18,185	18,207
Monthly lag of range of temperature	0.0001	A	18,174	18,195
Absolute dew point	0.0001	A	18,157	18,179
Two-week lag of ambient temperature	0.0001	A	18,134	18,156
Monthly lag of wind speed	0.0001	A	18,080	18,103

[1]Variable with 13,739 observations. Units are ˚C for ambient temperature, range of temperature and dew point, m/s for wind speed and W/m^2 for solar radiation. A= addition
[2]AIC = Akaike information criterion
[3]BIC = Bayesian information criterion

Table 4.7. Main effects and all possible interactions

Variable[1]	F-value	P-value
Base model		
Week of the year	29.28	0.0001
DMI	12.94	0.0003
BW	287.61	0.0001
NEm	69.95	0.0001
Monthly lag of solar radiation	3.08	0.0794
Monthly lag of range of temperature	27.86	0.0001
Absolute dew point	106.67	0.0001
Two-week lag of ambient temperature	5.14	0.0233
Monthly lag of wind speed	13.14	0.0003
Monthly lag of solar radiation × Monthly lag of range of temperature	7.91	0.0049
Monthly lag of solar radiation × Absolute dew point	9.45	0.0021
Monthly lag of solar radiation × Two-week lag of ambient temperature	19.83	0.0001
Monthly lag of solar radiation × Monthly lag of wind speed	14.14	0.0002
Monthly lag of range of temperature × Absolute dew point	96.24	0.0001
Monthly lag of range of temperature × Two-week lag of ambient temperature	2.83	0.0926
Monthly lag of range of temperature × Monthly lag of wind speed	6.57	0.0104
Absolute dew point × Two-week lag of ambient temperature	74.48	0.0001
Absolute dew point × Monthly lag of wind speed	4.69	0.0303
Two-week lag of ambient temperature × Monthly lag of wind speed	0.42	0.5167

[1]Variable with 13,739 observations. Units are kg for BW, Kg/d for DMI, Mcal/kg^{-d} for NEm, ˚C for ambient temperature, range of temperature and dew point, m/s for wind speed and W/m^2 for solar radiation.

Table 4.8. Main effects and significant interactions of final model using REML estimation

Variable[1]	Estimates	SE[2]	F-value	P-value
Intercept	-3.9298	0.4948	-7.94	0.0001
Base model				
Week of the year			33.39	0.0001
DMI	0.01031	0.002746	14.10	0.0002
BW	0.002927	0.000173	286.10	0.0001
NEm	1.0127	0.1218	68.91	0.0001
Monthly lag of range of temperature	0.2609	0.04637	31.65	0.0001
Absolute dew point	-0.07644	0.005621	184.93	0.0001
Two-week lag of ambient temperature	-0.00838	0.003195	6.87	0.0088
Monthly lag of wind speed	0.3182	0.09289	11.73	0.0006
Monthly lag of solar radiation × Monthly lag of range of temperature	-0.00030	0.000103	8.44	0.0037
Monthly lag of solar radiation × Absolute dew point	0.000069	0.000023	9.38	0.0022
Monthly lag of solar radiation × Two-week lag of ambient temperature	-0.00009	0.000023	16.39	0.0001
Monthly lag of solar radiation × Monthly lag of wind speed	-0.00139	0.000326	18.21	0.0001
Monthly lag of range of temperature × Absolute dew point	0.006527	0.000596	120.06	0.0001
Monthly lag of range of temperature × Monthly lag of wind speed	-0.03221	0.009969	10.44	0.0012
Absolute dew point × Two-week lag of ambient temperature	-0.00112	0.000123	82.76	0.0001

[1]Variable with 13,739 observations. Units are kg for BW, kg/d for DMI, Mcal/kg^{-d} for NEm, ˚C for ambient temperature, range of temperature and dew point, m/s for wind speed and W/m^2 for solar radiation.
[2]SE = Standard error

4.4.4. How Weather Variables Interacted to Affect ADG

4.4.4.1. Monthly Lag of Solar Radiation and Monthly Lag of Range of Temperature Interacted to Influence ADG

We observed a decrease in ADG with increasing solar radiation and increasing range of temperature (Figure 4.1.). Solar radiation has been reported to affect cattle. That is why shaded cattle have been observed to perform better than unshaded cattle. A classic study by Kelly et al. (1950) examined the influence of different thermal sources on a shaded animal. Kelly et al. (1950) observed that 28% of the radiant heat load experienced by the animal came from the sky, 21% from the shade material, 18% from the sunny ground, and 33% from the shaded ground.

This shows how much solar radiation contributes to the heat load of animal even when some shade is provided. A study by Bond et al. (1967) concluded that providing simple shade by intercepting the sun can reduce heat load as a result of radiant heat by 30% or more. The study by Bond et al. (1967) examined the radiation of the sun using a spherical and flat surface under the shade and in the sun to estimate how much radiation of sun is absorbed by animals. It was observed that one fifth to one-quarter of the total radiant flux of either shape under the shade was energy with wavelengths of $\leq$ 5μm. These wavelengths are the diffuse short wavelength solar energy. This shows that even when an animal is shaded and prevented from the direct exposure to sunlight, it is still exposed to large amount of diffuse solar energy which affects their body temperature or make them become stressed in hot weather. If cattle does not dissipate the heat effectively, they could become heat stressed and will have to reduce metabolic heat production by reducing feed intake which could all overall affect the growth of the animal. Morrison (1983) reported that heat stress lowers milk production and growth rate in cattle. Cattle in North America have been reported to be affected more negatively by heat stress as compared to cold stress. Cold fluctuating temperature could also change the thermal balance of the animals because acclimatization is not a fast process, it is gradual, and the process occurs in 2 phases (acute and chronic). It involves changes in secretion rate of hormones and receptors population in target tissues. Shae and Joleen (2012) examined the weather risk effect on cattle production and profitability in North Dakota. Shae and Joleen (2012) reported that there was a decrease in ADG of 0.06 - 0.08 kg/d for every day increase in cold stress. This indicates the effects of thermal environment of ADG. Fluctuation in temperature as a result of too rapid cooling of the environmental temperature and too rapid rate of heat loss by the animal could lead to hypothermia and on the other hand, too rapid rate of heating up and too slow of a loss of heat by the animal could lead to hyperthermia (NRC, 1981).

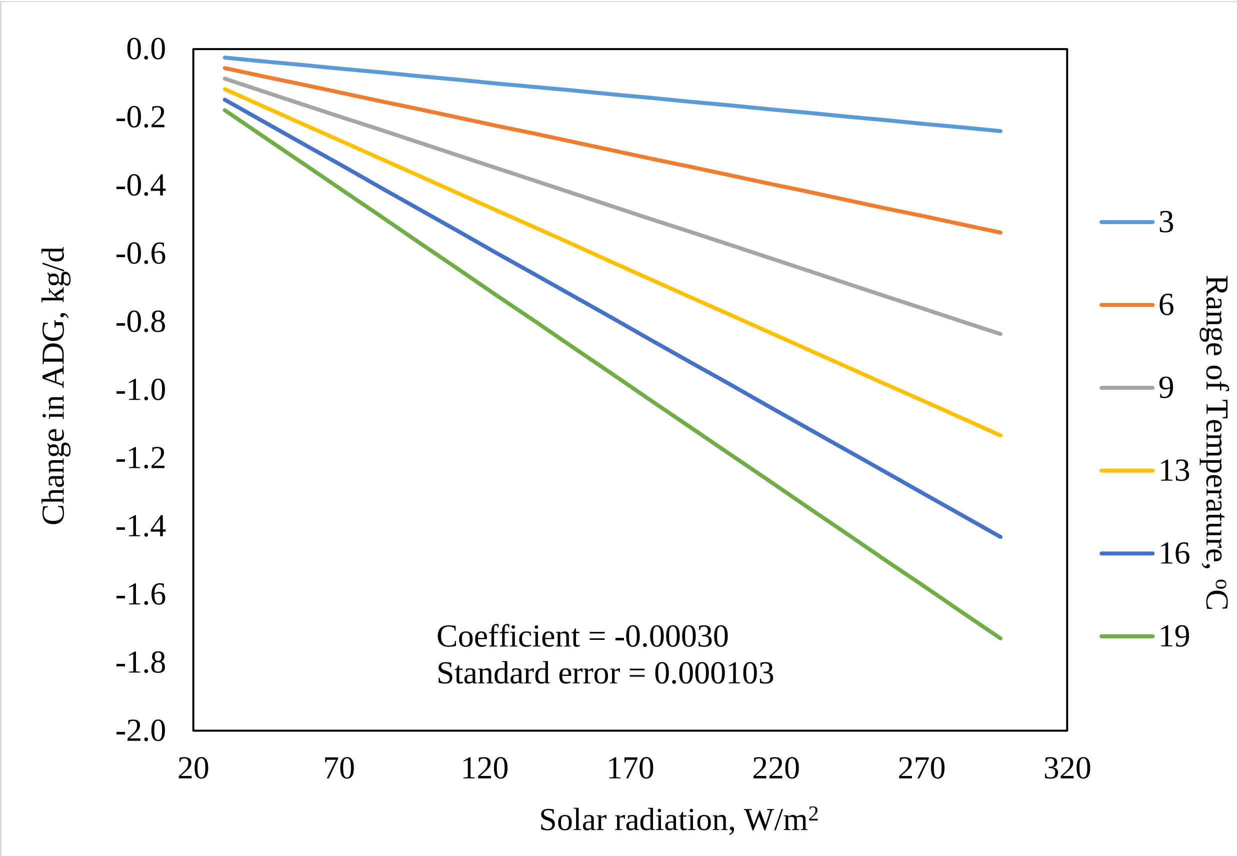

Figure 4.1. The effect of the interaction between solar radiation and range of temperature on ADG

4.4.4.2. Monthly Lag of Solar Radiation Interacted with Dew Point to Affect ADG

In this study, at dew points below -2.5 ˚C, and increasing solar radiation, there was an observed increase in ADG. On the other hand, with dew point temperature above 5.9 ˚C and increasing solar radiation, ADG decreased (Figure 4.2). The radiant energy from the sun has been known to influence the thermal energy of the animal. Cattle raised in the Northern Great Plains experience long winters characterized by prolonged periods of cold. These long periods of cold increase the maintenance energy requirement of the animals and has been reported to the largest investment of food energy in the cattle production system (Malechek and Smith, 1976).

With all the studies over the years, the exact knowledge of the processes of acclimatization to cold by large domestic animals is generally incomplete (Webster, 1974). We believe solar radiation increases the thermal energy of the cattle in the Northern Great Plains in the winter from the radiant heat absorbed by the animal's body which in turn reduces the cold stress experienced by the cattle. It has been reported that cattle in the Northern Great Plains have a behavioral response of orienting the body to the sun to maximize irradiative heat gain on cold, sunny days and this contributes some energy to the animal's thermal balance (Walsberg, 1992). It also makes sense that the amount of moisture in the air interacts with the radiant energy of the sun since overall, it has been reported that high amount of moistures in the air hinders the ability of the animal to dissipate heat during heat stress. The observed interaction between solar radiation and dew point on ADG influences the thermal balance of the animal which in turn affects the gain of the animal since animals must acclimate to short term- deviations from the running average of environmental conditions in a constantly changing winter environment (Senft and Rittenhouse, 1985). How weather variables interact together have been studies by other authors, Hahn (1985) examined the impact of weather on beef cattle, they concluded that temperature alone cannot be attributed to the death of the animals that occurred in their study. Hahn (1985) summarized that humidity, precipitation, and solar radiation are strong modifiers of the thermal environment.

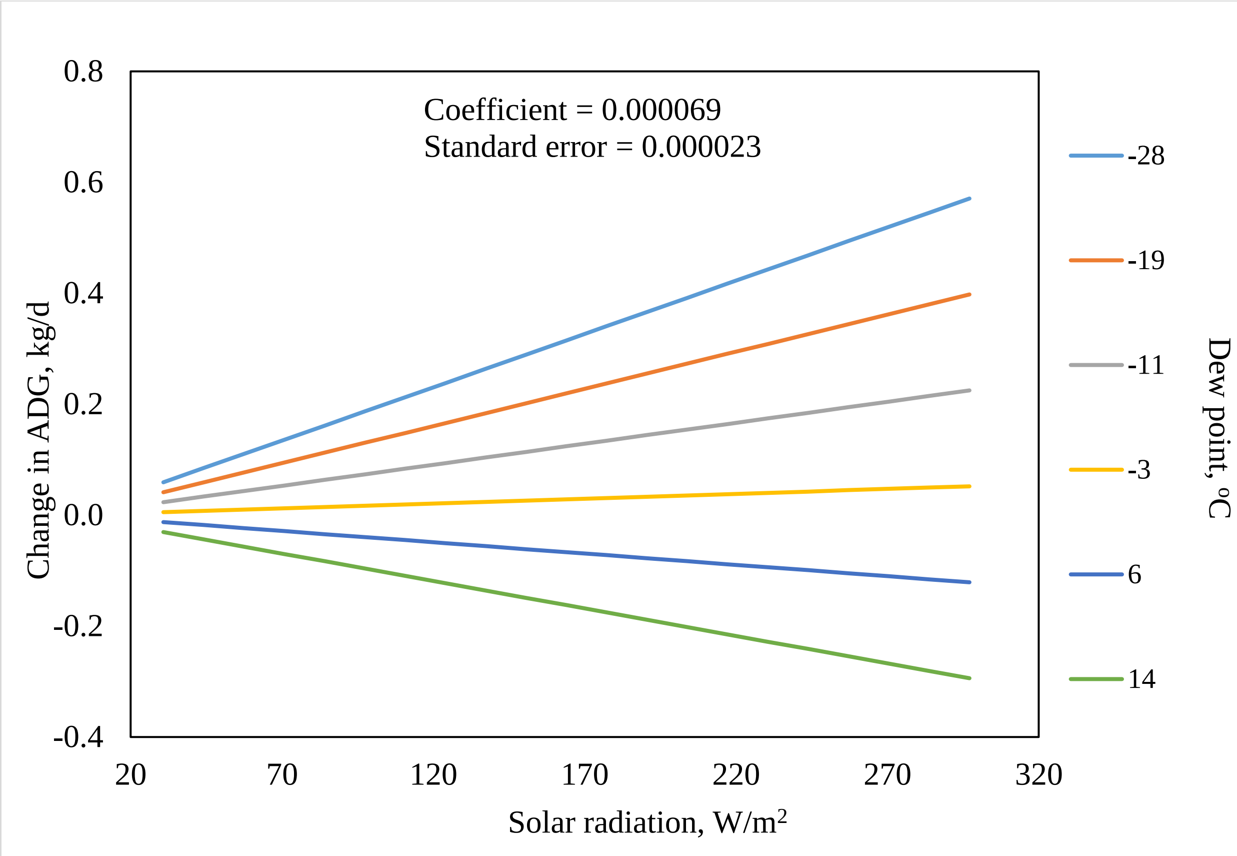

Figure 4.2. The effect of the interaction between solar radiation and dew point on ADG

4.4.4.3. Monthly Lag of Solar Radiation Interacted with Two-Week Lag of Ambient Temperature to Affect ADG

Solar radiation and temperature interacted to affect ADG. There was an increase in ADG with increasing solar radiation and decreasing temperature (< -5.7 ˚C). ADG decreased with increasing temperature and increasing solar radiation (Figure 4.3.). This describes the impact of ambient temperature and solar radiation as a thermal stressor on cattle. Some studies have shown that there is a strong relationship between ambient temperature and solar radiation, and it negatively affects the efficiency of cattle (Olson, 1938, Mader et al. 2010). Solar radiation is absorbed by the environment, the ground, and the cattle body. Solar radiation has been reported to directly affect the surface an animal has contact with as well as the temperature of the animal, especially in dark-hided cattle (Mader et al., 2006). The nature and temperature of the floor or other contact surfaces have also been reported to determine the rate of heat flow from an animal (NRC, 1981). Yusuf et al (2020) examined the influence of solar radiation and ambient temperature on DMI in beef cattle. In their study, they observed that solar radiation and ambient temperature interacted to affect DMI. This is similar to what is observed in this study. If solar radiation interacted to affect DMI, therefore it would most likely affect ADG since ADG is correlated with DMI. A study by Keren and Olson (2006) examined the thermal balance of cattle grazing winter range, they reported that cattle can mitigate the effect of extreme cold weather by using short-term behavioral responses like orienting to the sun's direct beam and seeking shelter from strong winds. This result is supported by the reports from NRC (1981) that stated that animals in sunlight gains some net energy of heat by thermal radiation that results in an increase in effective ambient temperature of between 3 - 5 $^{\circ}$C which is beneficial for animals in the Northern Great plains and could result in efficient energy use indirectly influencing ADG.

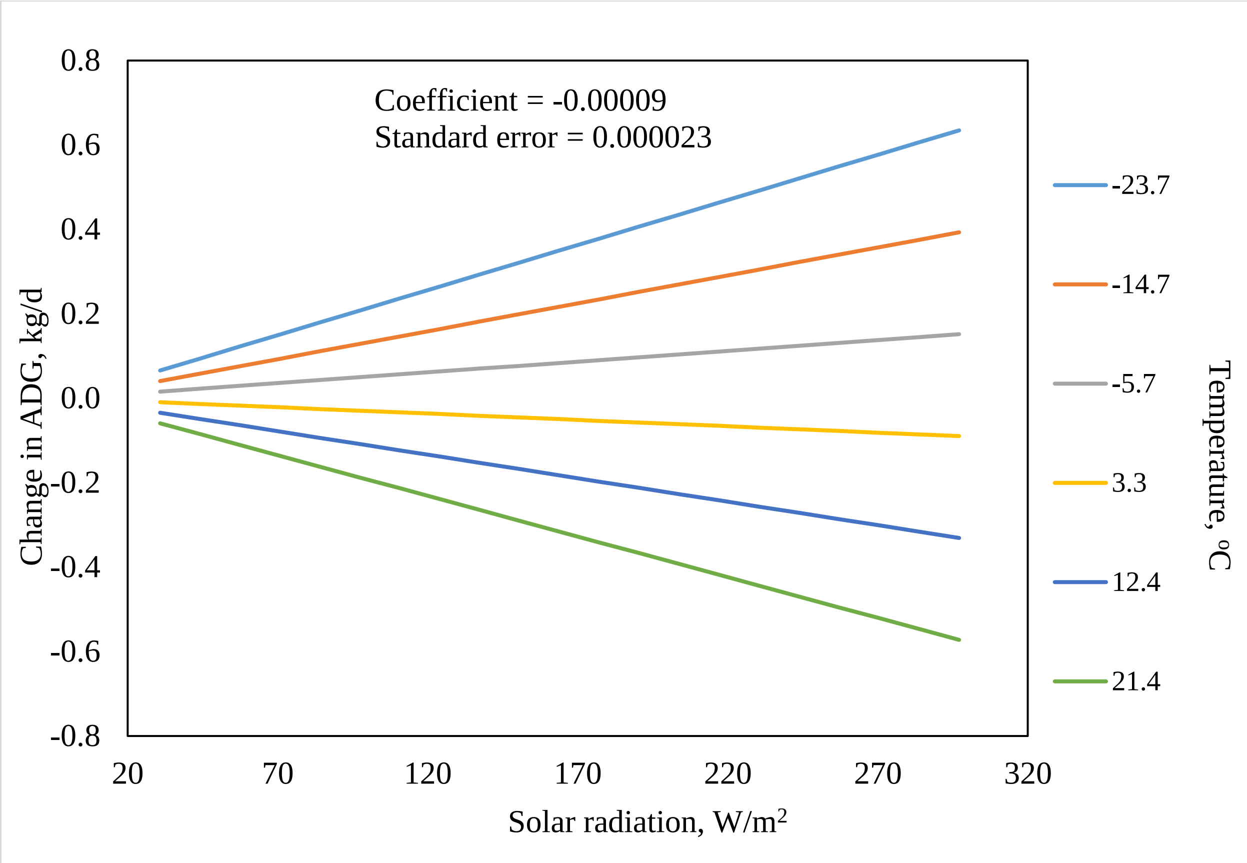

Figure 4.3. The effect of the interaction between solar radiation and temperature on ADG

4.4.4.4. Monthly Lag of Solar Radiation Interacted with Monthly Lag of Wind Speed to Affect ADG

Solar radiation and wind speed interacted to affect ADG. There was a decrease in ADG with increasing solar radiation and increasing wind speed (Figure 4.4). In cold weather, it is less clear if environmental modifications such as the use of shelter or wind breaks to minimize the effects of weather extremes could be beneficial for other purposes besides combating cold stress as a result of wind. It has been reported that wind has an influence on the thermal environment. In the cold environment, high winds make the temperature feel colder which is generally regarded as wind chill (Ames and Insley, 1975). Solar radiation and wind speed are known to contribute to the amount of thermal stress experienced by cattle. Walsberg (1992) reported that solar radiation can contribute 1000 W/m^2 to the total heat load of an animal. Mader and Davis (2004) in a study accounted for wind speed and solar radiation using temperature humidity index (THI). Mader and Davis (2004) observed that for each 1 m/s increase in wind speed, THI was reduced by 3.14 units and on the other hand for each 100 W/m^2 decrease in solar radiation, THI was reduced by 1.49 units. This shows how wind speed and solar radiation affect the thermal balance of the environment which has a direct effect on the animal. Wind speed has been reported to help the animal dissipate heat. In a report by NRC (1981), they observed that when wind speed goes below 2 m/s, the ability of the animal to dissipate heat is reduced but Mader and David (2004) observed that even above 2 m/s, wind speed could still be beneficial in heat dissipation since they did not observe any quadratic or curvilinear relationship in their model.

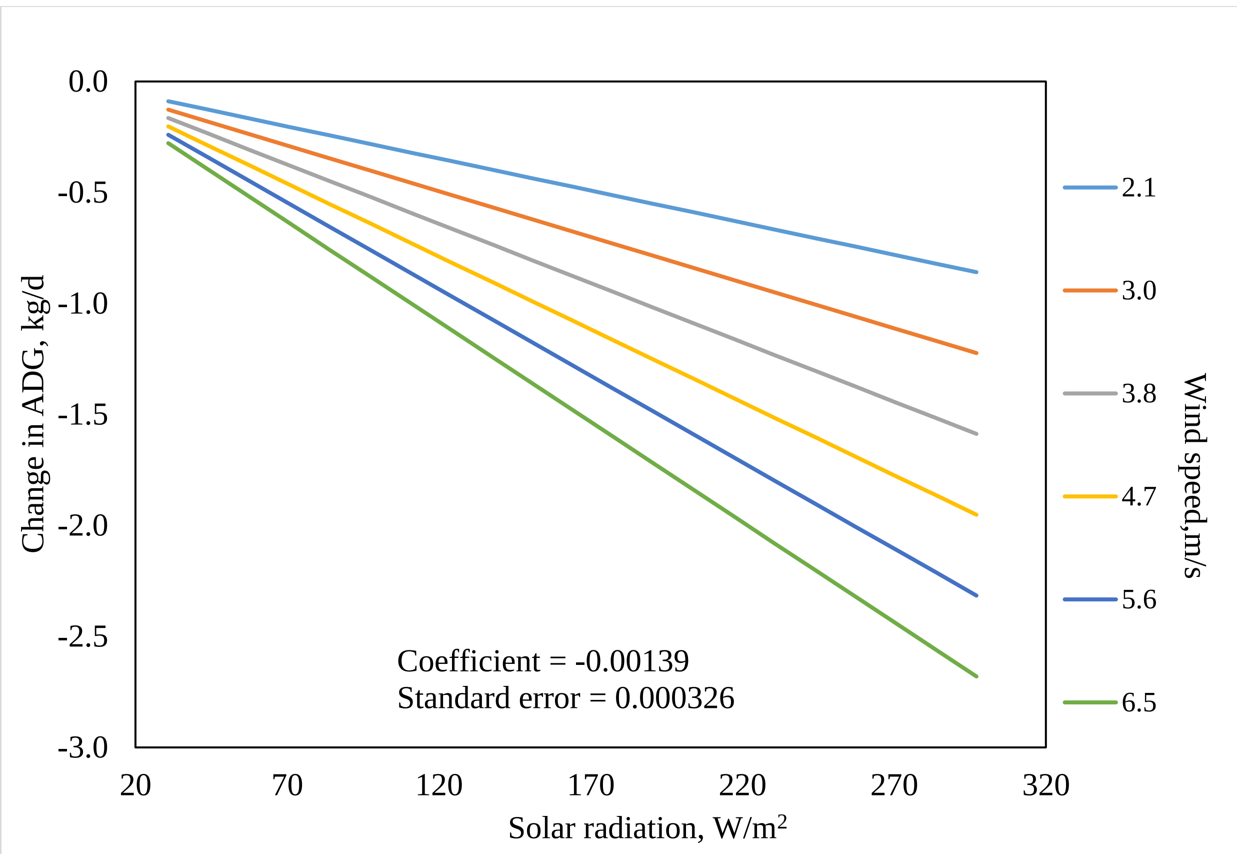

Figure 4.4. The effect of the interaction between solar radiation and wind speed on ADG

4.4.4.5. Monthly Lag of Range of Temperature Interacted with Absolute Dew Point to Affect ADG

The interaction between range of temperature and dew point and its effect on ADG is shown in Figure 4.5. ADG increases with increasing dew point temperature and increasing range of temperature. On the other hand, ADG decreases with decreasing dew point temperature and increasing range of temperature. This shows that fluctuation in temperature has an impact on the animal because cattle generally take time to fully acclimatize to cold weather. Short term responses to fluctuation in weather may include change in DMI to compensate for the change in the thermal environment which in turn will affect their ADG if the net heat loss is higher than the net heat gained. Fluctuation in temperature and its thermal impact on the animal could be further exacerbated by the amount of moisture in the air. Animals rely on evaporative cooling during hot weather, therefore if the dew point is high, evaporative cooling by the animal may be hindered which results in more thermal stress on the animal which in turn affects the animal's production. Hill and Wall (2015) examined the influence of weather variables on milk yield and composition of dairy cows in a temperate environment. In the study by Hill and Wall (2014), they observed a decline in milk protein as temperature humidity index increases. The temperature humidity index in which the milk protein started declining in their study was lower than other similar studies (Ravagnolo et al., 2000; Gauly et al., 2013). They attributed the differences observed in their study and the other studies to the adaptation of the animals to heat in other studies compared to theirs. This shows that animals in temperate environments adapted to the cold environment when exposed to heat stress as a result of temperature humidity interaction could have a lower tolerance which could cause a decline in their production. We believe this is similar in beef cattle also, the upper critical temperature of cattle in colder temperate regions like North Dakota is lower and as a result they could become heat stressed faster when temperature fluctuates.

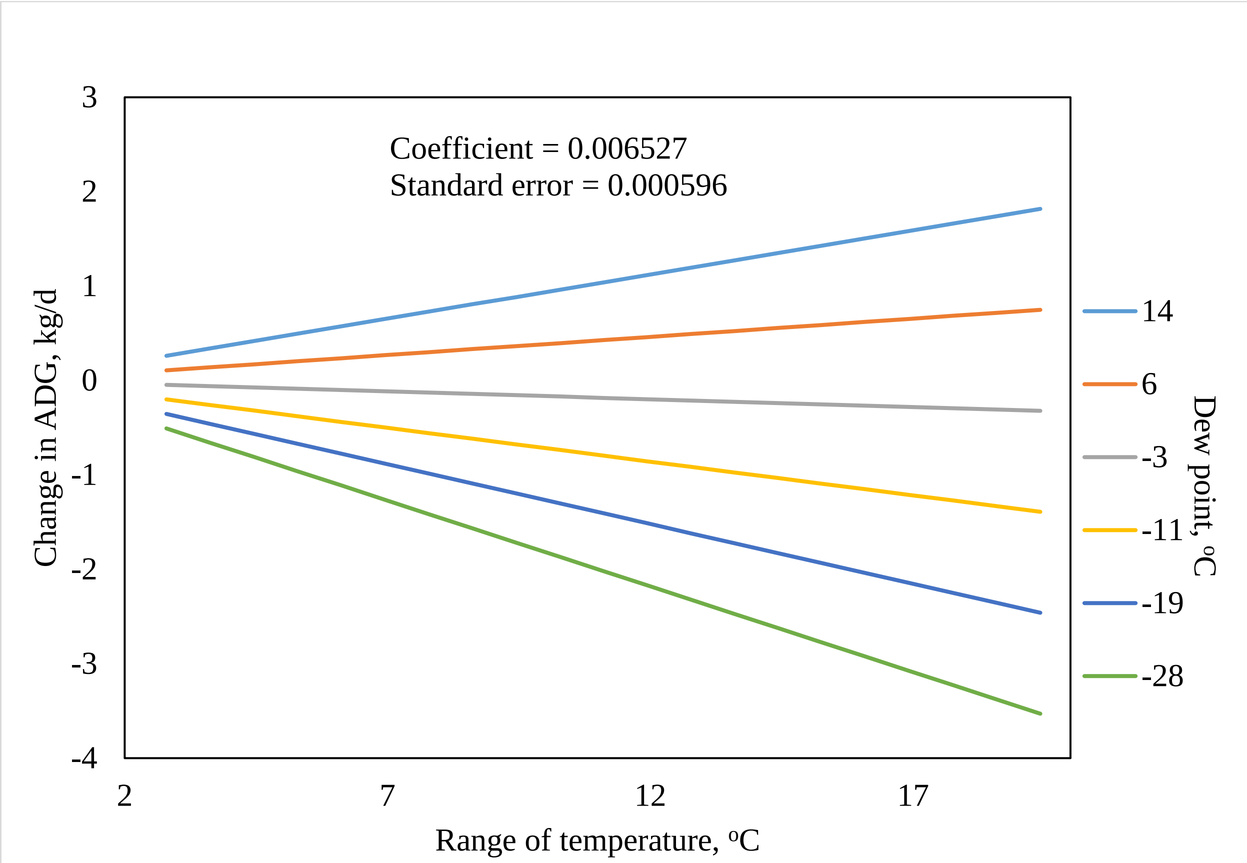

Figure 4.5. The effect of the interaction between range of temperature and dew point on ADG

4.4.4.6. Monthly Lag of Range of Temperature Interacted with Monthly Lag of Wind Speed to Affect ADG

The interaction between monthly lag of range of temperature and monthly lag of wind speed and its effect on ADG is shown in Figure 4.6. As range of temperature and wind speed increased, ADG decreased up to 4.0 kg/d. This explains that wind speed increases the effect of variation in temperatures on the growth of animal. Cold and fluctuating temperature has been reported to cause cold stress in animals especially when it is accompanied with high winds. Constable et al (1999) reported that cold air temperature and excessive wind or humidity are major stressors in newborn calves because of their small body insulation and increases body surface and body mass ratios. Fluctuation in temperature and its interaction in dew point as observed in this study could impact ADG since the steers will have to divert energy to provision of warmth and production of more hair coat to decrease the effect of the cold stress. A study by Mark and Schroeder (2002) examined the effect of weather on average daily gain and profitability. Mark and Schroeder (2002) reported observing a reduced profit of $0.15/head for cattle fed during winter when there is 1% increase in the percent of days with cold stress (low temperature and high wind speeds). This shows temperature and wind speed interacts to affect the productivity of cattle and subsequently decreases profit margin for the producer. Other authors such as Davis and Mader (2003) recognized the influence of wind speed on temperature. In their model, they gave an adjustment of 1.072 units decrease in THI for every 1.61 km/hr increase in wind speed. NRC (2001) reported that in extreme cold situations, DMI does not increase at the same rate as metabolism, for this reason, animals are in a negative energy balance, and therefore divert the energy which would have been used for gain or production to heat for warmth. During the review of literature, there are no studies that have examined the influence of range of temperature on DMI intake and this study has shown that range of temperature (fluctuating temperature) and wind speed impacts DMI in steers.

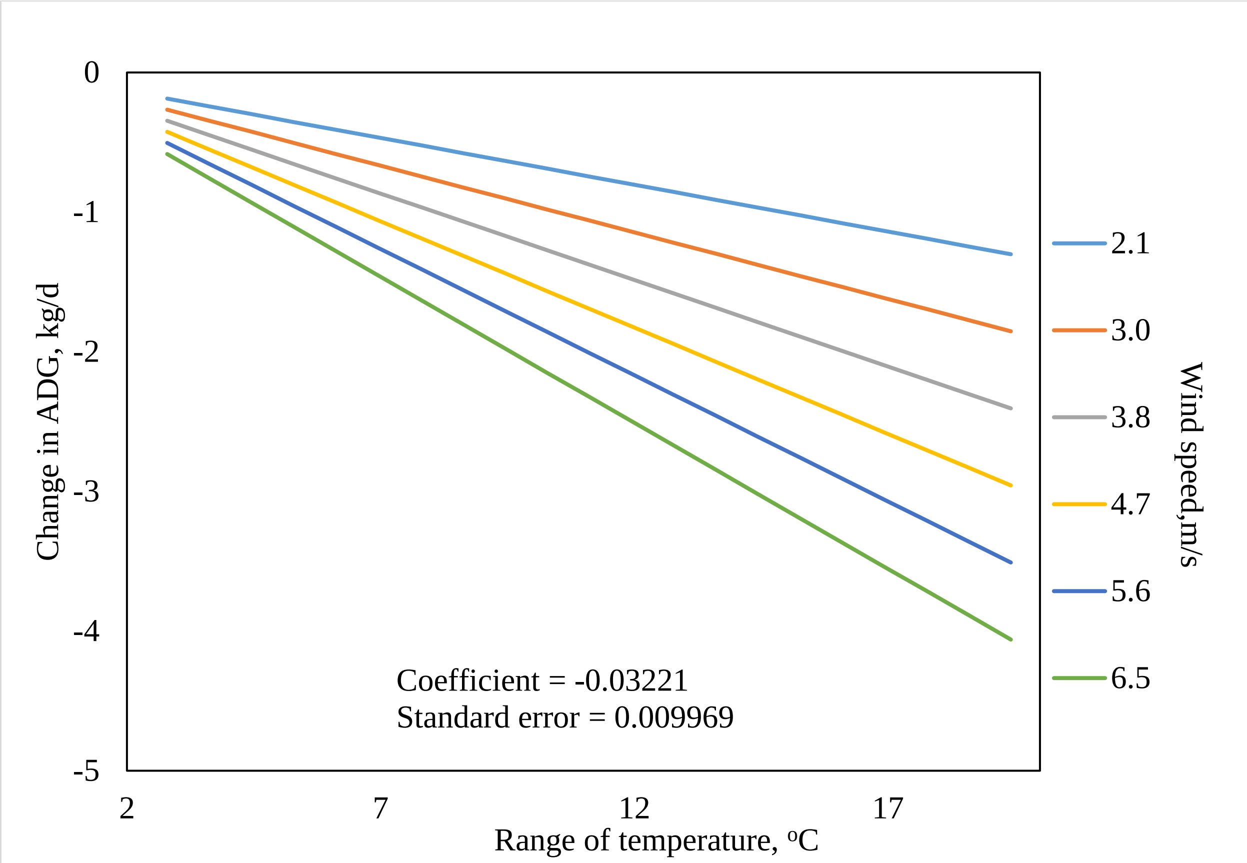

Figure 4.6. The effect of the interaction between range of temperature and wind speed on ADG

4.4.4.7. Dew Point and Two-Week Lag of Ambient Temperature Interacted to Affect Ambient Temperature

Dew point and two-week lag of ambient temperature interacted to affect ambient temperature (Figure 4.7). Low (-27.8 ˚C) dew point temperature and low ambient temperature (-23.7˚C), negatively influenced ADG. As temperature reached 3.3˚C, dew point had a small effect on ADG. When temperature was 21.4 ˚C, dry dew point increased gain but wet dew point decreased gain. This shows that low dew point impacts ADG positively to a certain point after which as temperature increases, it gradually results to decreased efficiency in the animal because of heat stress. Dew point which is a measure of the amount of moisture in the air has been shown to reduce the effective insulation of an animal’s coat (Blaxter and Wainman 1964; Webster and

Park, 1967; Ames et al., 1975). It has been reported that animals unfortunately reduce their DMI during inclement weather which even makes them more susceptible to cold. However, it was expected that the animals in this study should have adapted to the extreme cold conditions and that could be why the impact of low dew point temperature and ambient temperature on their ADG was not high. Dill and Irving (1964) reported that cold adapted animals suffer less in extreme cold than similar non adapted animals. Reduction in feed efficiency in winter fed animals has long been known. Elam (1971) compared efficiency between summer and winter fed animals in commercial feedlots in southern California and midwestern states. Elam (1971) reported a 14 to 20 % lower feed to gain ratio by the feedlot cattle in California during winter. This shows that energy demand of the cattle during winter increases because of cold temperature and it impacts their growth performance.

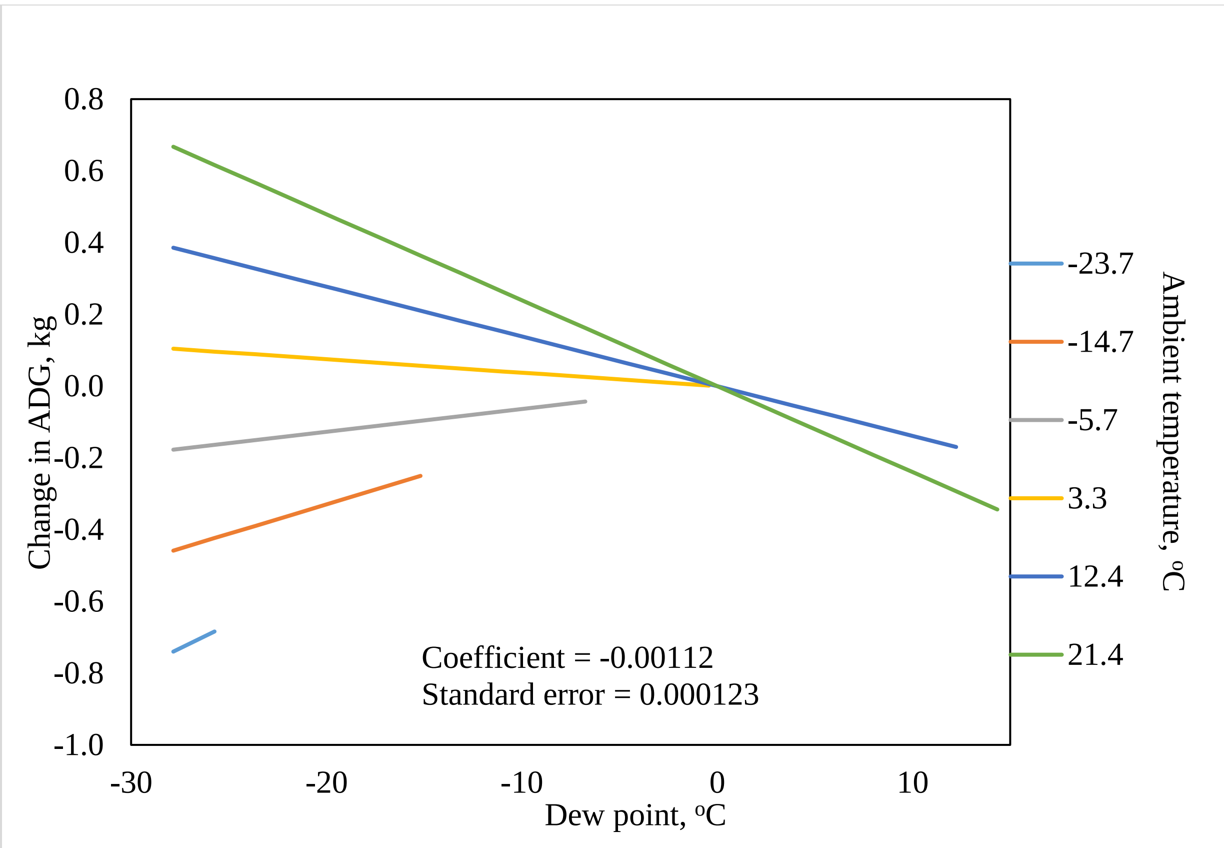

Figure 4.7. The effect of the interaction between dew point and ambient temperature on ADG

4.5. Conclusion

Weather has a significant impact on cattle raised in the Northern Great Plains and their productivity is affected as a result of the changes in energy demand and the thermal effects of weather exerted on them. Weather variables are complex and interact with each other to affect ADG of cattle. In this study absolute dew point was the greatest single main effect that affected ADG. Solar radiation interacted with range of temperature, dew point, ambient temperature, and wind speed and all other interactions accounted for some variation in ADG. Monthly lag of range of temperature and ambient temperature both interacted with dew point and were the two sets of interactions that accounted for the greatest variation in ADG from all the interactions modelled.

4.6. Implications

There are no ADG models that accounted for the effect of weather variables in their equations. This study has showed that weather variables influence ADG and will improve current ADG models. Improving predictions of ADG, which is an important measure of productivity used by beef cattle producers, will enhance the overall efficiency of their enterprise.

4.7. Literature Cited

Ames, D. R., and L. W Insley. 1975. Wind-chill effect for cattle and sheep. J. Anim. Sci. 40:1 DOI: 10.2527/jas1975.401161x

Archer J. A., Pitchford W. S. Hughes T. E. Parnell P. F. 1998. Genetic and phenotypic relationships between food intake, growth, efficiency, and body composition of mice post weaning and at maturity. Anim. Sci.67:171–182. DOI: https://doi.org/10.1017/S1357729800009917

Basarab J., McCartney D., Okine E. K., and V. S Baron. 2007. Relationships between progeny residual feed intake and dam productivity traits. Can. J. Anim. Sci.87:489–502. DOI: https://doi.org/10.4141/CJAS07026

Blaxter, K. L., and F. W. Wainman. 1964. The effect of increased air movement on the heat production and emission of steers. J. Agric. Sci. 62:207-214 DOI: https://doi.org/10.1017/S0021859600060822

Bond, T. E., Kelly, C. F., Morrison, S. R., and N. Pereira (1967). Solar, atmospheric and terrestrial radiation received by shaded and unshaded animals. Transactions of American Society of Agricultural Engineers 10:622-7 DOI:10.13031/2013.39745

Constable, P. D., P. G. Walker, D. E. Morin, and J. H. Foreman. 1999. Use of fetlock temperature to determine need for intravenous fluids in dehydrated calves. Accessed: June 23, 2021.http://www.livestocktrail.illinois.edu/dairynet/paperdisplay.cfm?contentid=302

Davis, S., and T. L Mader. 2003. Adjustments for Wind Speed and Solar Radiation to the Temperature-Humidity Index". Nebraska Beef Cattle Reports. 224. https://digitalcommons.unl.edu/animalscinbcr/224

Dill, P. B., and L. Irving. 1964 Polar biology, Handbook of Physiology, Chapter 5, American Physiological Society

Elam, C. J. 1971. Problems related to intensive indoor and outdoor production systems. J. Anim. Sci. 32:554. DOI: https://doi.org/10.2527/jas1971.323554x

Gauly, M., Bollwein, H., Breves, G., Bruegemann, K., Daenicke, S., Das, G., Demeler, J., Hansen, H., Isselstein, J., Koenig, S., Lohoelter, M., Martinsohn, M., Meyer, U., Potthoff, M., Sanker, C., Schroeder, B., Wrage, N., Meibaum, B., von Samson-Himmelstjerna, G., Stinshoff, H and C. Wrenzycki.2013. Future consequences and challenges for dairy cow production systems arising from climate change in Central Europe – a review. Animal 7, 843–859 DOI: 10.1017/S1751731112002352

Hahn, G. L. 1985. Weather and Climate Impacts on Beef Cattle. Roman L. Hruska U.S. Meat Animal Research Center. 67. https://digitalcommons.unl.edu/hruskreports/67

Hill, D., and E. Wall. 2015. Dairy cattle in a temperate climate: The effects of weather on milk yield and composition depend on management. Animal 9:138–149. DOI: https://doi.org/10.1017/S1751731114002456

Kelly, C. F., Bond, T. E., and N. R. Ittner. 1950. Thermal design of livestock shades. Agricultural Engineering 31:601-606. Retrieved from https://calag.ucanr.edu//download_pdf.cfm?article=ca.v008n08p3 on May 15th, 2021.

Keren, E. N., and B. E Olson. 2006. Thermal balance of cattle grazing winter range: Model development. J. Therm. Biol. 31:371-377 DOI: 10.1016/j.jtherbio.2005.11.029

Lofgreen, G. P., and W. N. Garett. 1968. A system for expressing net energy requirements and feed values for growing and finishing beef cattle. J. Anim. Sci. 27:793-806 DOI: https://doi.org/10.2527/jas1968.273793x

Mader T., and S. Davis. 2004. Wind speed and solar radiation corrections for the temperature-humidity index. Retrieved from https://ams.confex.com/ams/pdfpapers/47453.pdf on June 22, 2021.

Mader, T. L., L. J. Johnson, and J. B. Gaughan. 2010. A comprehensive index for assessing environmental stress in animals. J. Anim. Sci. 88:2153-2165. DOI: 10.2527/jas.2009-2586

Mader, T. L., M. S. Davis, and T. Brown-Brandl. 2006. Environmental factors influencing heat stress in feedlot cattle. J. Anim. Sci. 84:712–719. DOI: 10.2527/2006.843712x

Malechek, J. C., and B. M Smith. 1976. Behavior of range cows in response to winter weather. J. Range Management. 29:9-12. DOI:10.2307/3897679

Mark, D. R. and Schroeder, Ted C. 2002. Effects of weather on average daily gain and profitability. Kansas Agricultural Experiment Station Research Reports: Vol. 0: Iss. 1. DOI: https://doi.org/10.4148/ 2378-5977.1748

Miller A. J., Faulkner D. B., Knipe R. K., Strohbehn D. R., Parrett D. F., and L. L Berger 2001. Critical control points for profitability in the cow-calf enterprise. Professional Anim. Sci.17:295–302. DOI: https://doi.org/10.15232/S1080-7446(15)31643-0

Montanholi, Y. R., K. C. Swanson, R. Palme, F. S. Schenkel, B. W. McBride, D. Lu, and S. P. Miller. 2010. Assessing feed efficiency in beef steers through feeding behavior, infrared thermography and glucocorticoids. Animal 4:692-701. DOI: 10.1017/S1751731109991522

Morrison, S. R. 1983. Ruminant heat stress: effect on production and means of alleviation. J. Anim. Sci. 57:594-600. DOI: 10.2527/jas1983.5761594x

NRC. 2001. Nutrients Requirement of Dairy Cattle. (7th Ed.). Nutrient requirement of domestic animals. National Academy Press, Washington, D.C

North Dakota Agricultural Weather Network Station (NDAWN). 2021. Available at https://ndawn.ndsu.nodak.edu/

NRC. 1981. Effect of Environment on Nutrient requirements of Domestic Animals. National Academy Press, Washington, DC.

Olson, T.M. 1938. Effect of sunlight on the growth, production, and reproduction of dairy cattle. Bulletins. Paper 319. http://openprairie.sdstate.edu/agexperimentsta_bulletins/319

Ravagnolo, O, Misztal, I and G. Hoogenboom. 2000. Genetic component of heat stress in dairy cattle, development of heat index function. J. Dairy Sci. 83:2120-2125 DOI: 10.3168/jds.S0022-0302(00)75094-6

SAS User's Guide: Statistics. 2004. SAS Institute Inc., Cary, NC.

Senft, R. L., and L. R. Rittenhouse. 1985. A model of thermal-acclimation in cattle. J. Anim. Sci. 61:297-306. DOI: 10.2527/jas1985.612297x

Shae, BillieJo A. and C. H. Joleen. 2012. Weather Risk Effects on Cattle Production and Profitability in North Dakota, 2012 Annual Meeting, August 12-14, 2012, Seattle, Washington 124883, Agricultural and Applied Economics Association

Swanson, K. C., A. Islas, Z. E. Carlson, R. S. Goulart, T. C. Gilbery, and M. L. Bauer. 2014. Influence of dry-rolled corn processing and increasing dried corn distillers grains plus solubles inclusion for finishing cattle on growth performance and feeding behavior. J. Anim. Sci. 92:2531-2537. DOI: 10.2527/jas.2013-7547

Walsberg G. E., 1992. Quantifying radiative heat gain in animals. Amer. Zool. 32, 217- 223. DOI: https://doi.org/10.1093/icb/32.2.217

Webster, A. J. F. 1974. Heat loss from cattle with particular emphasis on the effects of cold. Pages 205-231 in heat loss from animals and man: assessment and control. J.L. Monteith and L.E. Mount, eds. Butterworths, London.

Webster, A. J. F., and C. Park. 1976. The effect of jute coats on the heat losses of two breeds of sheep exposed to different environments. Anim. Prod. 9:484. DOI: https://doi.org/10.1017/S0003356100042057

Yusuf, M., K. C. Swanson, L. L. Hulsman Hanna, R. Degges, and M. L. Bauer. 2020 Solar radiation as a predictor variable for dry matter intake in beef steers. J. Anim. Sci. 98:31. DOI: https://doi.org/10.1093/jas/skaa054.055

Zinn, R. A., and Y. Shen. 1998. An evaluation of ruminally degradable intake protein and metabolizable amino acid requirements of feedlot calves. J. Anim. Sci. 76:1280-1289 DOI: 10.2527/1998.7651280x

CHAPTER 5. HOW WEATHER VARIABLES INFLUENCED DRY MATTER INTAKE (DMI) OF BEEF COWS

5.1. Abstract

Models that can predict dry matter intake (DMI) of cows will help in efficient allocation and management of feed resources. A study was undertaken to understand the relationship between weather variables and DMI of beef cows in the Northern Great Plains of North America. Data from 155 beef cows with 2,161 observations (cow-weeks) was utilized. The variables utilized for this study were BW (455.10 to 875.43 kg), DMI (9.03 to 27.69 kg/d), NEm intake (9.16 to 46.12 Mcal/d), ambient temperature (-18.86 to 23.88°C), range of temperature (4.54 to 13.82 °C), wind speed (2.29 to 5.39 m/s), solar radiation (30.97 to 292.61 W/m^2) dew point (-21.42 to 19.15 °C), and two-week lag (average of previous two week's values) and monthly lag (average of previous four weeks values) of each weather variable. Residuals of DMI fitting week of the year (fixed), and treatment (random), were used to generate scatter plots to identify if linear relationships existed. BW and other weather variables had a linear relationship with DMI, while NEm intake had both linear and quadratic relationships with DMI. For the model, MIXED linear regression of SAS was used using stepwise regression. Model fits were determined using P-values, AIC, and BIC values. Absolute ambient temperature and range of temperature were weather predictors ($P < 0.05$) of DMI. Wind speed interacted ($P < 0.05$) with ambient temperature and range of temperature, and this accounted for additional variation in DMI of beef cows. These results help to gain more understanding of the relationship between weather variables and DMI in beef cows.

5.2. Introduction

Feed intake in ruminants, especially cows, is complex and having models that will reliably explain the control of feed intake has been challenging. Feed intake models that can predict dry matter intake (DMI) of cows are useful tools for efficient utilization and allocation of feed resources to cows. Cow's DMI is difficult to predict because of frequent fluctuation in their intake caused by hormonal changes which could be due to estrus, pregnancy, and lactation. There has been reliance on empirical models because of the complexity of DMI control and lack of availability of adequate, mechanistic models (Gunter, 2017). The available empirical models (NRC, 1981; NRC 2000; NASEM, 2016) have only been able to typically account for around 50 to 70 % of the variation in intake with standard errors of around 5% which can be attributed as relatively high (Gunter, 2017). At the same time, these models have not been adequate for cows in extremely cold environment like the Northern Great Plains. These models also do not account for some weather variables that might interact together to affect DMI of beef cows. There is a difference in the intake of cows compared with growing animals and so there is a need for models that can account accurately estimate the intake of cows. There is also a difference in cows fed roughage diets with supplements. In this study, the cows were fed intensively. The objective of this study is to understand which weather variables affect DMI of beef cows and identify the weather variables that are more important in predicting DMI of beef cows.

5.3. Materials and Methods

5.3.1. Data Collection

Data used for this experiment were collected from the Beef Cattle Research Complex of North Dakota State University, Fargo, North Dakota located at latitude 46.9027853 degrees North and longitude -96.8418183 degrees West. An Insentec feeding system (RIC feeding system; Hokofarm Group, Marknesse, The Netherlands), which records the amount of feed intake, number of visits, time of visit and meals for each animal, was used for the data collection. The data used were from 3 experiments that were conducted in years 2011, 2015 and 2020 (Table 5.1).

Table 5.1. Experiments used in this study

Year (week of the year)		n[1] of cows	n of cow-week observations	Breed[2]	Publication
Start	End				
2011 (wk. 43)	2012 (wk. 2)	48	530	AN, SM, SH, and Crossbred	Klein et al., 2014
2015 (wk. 44)	2016 (wk. 18)	47	1,181	AN	Tanner et al., 2020
2020 (wk. 28)	2012 (wk. 36)	57	450	AA, AN, SH, SM, and crossbred	Mosher et al. 2021

[1]n=number.
[2]AN= Angus, SM = Simmental, SH = Shorthorn, AA = America Aberdeen.

5.3.2. Weather Data

Data for weather variables were obtained from the North Dakota Agricultural Weather Network (NDAWN) station for each experiment period included in this study. Each NDAWN station is assumed to adequately represent all weather conditions, except rainfall, in a 32 km radius (NDAWN, 2021). The NDAWN station, which is 2.33 km from the BCRC, provides five-minute averages, hourly averages, daily, monthly, and yearly summaries for each supported weather variable (NDAWN, 2021). For this study, daily summaries of each weather variable were used for each experiment period included.

Weather variables modeled for this study included:

- Ambient temperature: the air temperature of the surrounding environment (°C)
- Absolute range in temperature: the difference between absolute minimum and absolute maximum temperature

- Dew point: the temperature at which water vapor in the air begins condensing to form liquid. The dew point temperature is calculated from the air temperature and relative humidity. Dew point temperature units are Fahrenheit or Celsius (NDAWN, 2021).
- Wind speed: average of all measured wind speeds during the hour for a period of 24 hours). Wind speed is measured every 5 seconds 10 meters above the soil surface with an anemometer (NDAWN, 2021).
- Solar radiation: total of all hourly totals of incident solar radiation energy for a 24-hour period from midnight to midnight (W/m^2) (NDAWN, 2021). Total incident solar radiation flux density is measured in $Watts/m^2$ at approximately 2 m above the soil surface with a pyranometer.
- The two-week lag and monthly lag of each weather variable was also considered. Two-week lag is the average of the previous two week's weather variable while monthly lag is the average of the previous month's weather variable in question.

5.3.3. Non-Weather Variables

The non-weather variables considered for this experiment include weekly average dry matter intake (DMI), weekly average body weight (BW), dietary net energy of maintenance intake (NEm intake), treatment, and the week of the year. Week of the year ranged from week 1 to 52.

5.3.4. Data Management

The daily feed intake data was averaged into weekly averages to reduce the day-to-day fluctuation. The weekly dry matter analysis of the diet fed from each experiment was matched with the weekly feed intake to calculate the actual DMI consumed by each animal. Weekly BW for each animal was calculated from the monthly BW data values by using simple linear regression. Values for all weather variables were converted into weekly averages. Dietary energy density (NEm) was estimated using diet composition in the Beef Cattle Nutrient Requirement Model by NASEM (2016). NEm concentration was multiplied by DMI to arrive at the NEm intake of each observation. The descriptive statistics of the variables used in this study is shown in Table 5.2.

Table 5.2. Descriptive statistics of the variables in this study

Variable[1]	Mean	Minimum	Maximum	SD[2]	SE[3]
BW, kg	693.29	455.1	887.53	72.14	1.56
DMI, kg/d	16.15	9.03	27.69	3.85	0.08
NEm intake, Mcal/d	23.57	9.16	46.12	7.64	0.16
Ambient temperature, ˚C					
No lag	3.56	-18.86	23.88	10.91	0.23
Two-week lag	4.15	-15.86	24.52	10.96	0.24
Monthly lag	4.72	-12.47	23.54	10.94	0.24
Range of temperature, ˚C					
No lag	9.93	4.54	13.82	1.99	0.04
Two-week lag	9.91	5.08	13.22	1.68	0.04
Monthly lag	10.05	6.32	12.82	1.67	0.04
Wind speed, m/s					
No lag	3.41	2.28	5.39	0.66	0.01
Two-week lag	3.44	2.50	4.81	0.57	0.01
Monthly lag	3.46	2.52	4.37	0.46	0.01
Solar radiation, W/m^2					
No lag	118.14	30.97	292.61	76.70	1.65
Two-week lag	118.22	34.56	288.62	74.93	1.61
Monthly lag	121.81	43.94	282.72	76.28	1.64
Dew point, ˚C					
No lag	-1.23	-21.43	19.15	10.22	0.22
Two-week lag	-0.71	-18.26	18.96	10.14	0.22
Monthly lag	-0.35	-14.81	17.78	9.88	0.21

[1]Variable with 2,161 observations.
[2]SD = Standard error.
[3]SE = Standard deviation.

5.4. Statistical Analysis

Data were analyzed as a repeated measures design using the MIXED procedures of (SAS Inst., Cary, NC) and within-individual relationship was accounted for using the Toeplitz covariance structure. Week of the year was used as fixed effect and experiment was included as a random effect to output the residuals. Correlation among weather variables was checked using the PROC CORR statement of SAS. Linear and quadratic effects of all the weather variables modeled were tested.

The model for fitting residuals, the base model and the final model were analyzed using the restricted maximum likelihood estimation method (REML), while the maximum likelihood (ML) was used in each step of the stepwise addition or removal of variables. Akaike information criterion (AIC) and Bayesian information criterion (BIC) values were used to assess model fit each time a variable was added to the model in a forward stepwise fashion. The parameter estimates were outputted using the solution statement. The full model was refitted using REML to obtain less biased estimates. For all the models, components with ($P < 0.05$), F-values, and their respective AIC and BIC values are reported.

5.5. Results and Discussion

The base model used in this study is shown in table 5.3. In the base model, week of the year (fixed effect), treatment (random effect), linear effect of BW, linear effect of NEm intake, and quadratic effect of NEm intake were included. The quadratic effect of BW was not significant in the model, so it was not included in the base model.

Table 5.3. Variables in the base model

Variable	Estimates	SE[1]	F-value	P-value
Week of the year	-	-	28.96	0.0001
BW, kg	0.0017	0.00055	9.43	0.0022
NEm intake, Mcal/day				
Linear	0.8413	0.02064	1661.57	0.0001
Quadratic	-0.00598	0.000367	265.43	0.0001

[1]SE= standard error, AIC = 5,022.3, and BIC = 5,020.7.

The individual addition of weather variables to the base model is shown in table 5.4. Except for wind speed, which had monthly lag of wind speed as the most significant form, all other weather variables had their absolute form as the most significant variable when added to the base model individually.

Table 5.4. Individual additions of variables to the base model

Variable[1]	F-value	P-value	AIC[2]	BIC[3]
Base model	-	-	5,022.3	5,020.7
Ambient temperature, ˚C				
No lag	5.15	0.0233	4,968.9	4,965.2
Two-week lag	1.08	0.2978	4,973.2	4,969.5
Monthly lag	1.17	0.2788	4,972.8	4,969.1
Solar radiation, W/m^2				
No lag	19.20	0.0001	4,955.5	4,951.7
Two-week lag	3.80	0.0510	4,970.6	4,966.8
Monthly lag	14.52	0.0001	4,960.3	4,956.6
Range of temperature, ˚C				
No lag	25.30	0.0001	4,949.6	4,945.9
Two-week lag	1.35	0.2447	4,972.7	4,968.9
Monthly lag	15.63	0.0001	4,958.9	4,955.2
Wind speed, m/s				
No lag	8.42	0.0041	4,966.4	4,962.7
Two-week lag	5.27	0.0218	4,969.3	4,965.6
Monthly lag	17.16	0.0001	4,958.3	4,954.6
Dew point, ˚C				
No lag	7.59	0.0059	4,966.8	4,963
Two-week lag	0.58	0.4478	4,973.4	4,969.7
Monthly lag	0.13	0.7220	4,973.8	4,970.1

[1]Variable with 2,161 observations.
[2]AIC = Akaike information criterion.
[3]BIC = Bayesian information.

The addition and removal of main effects in a stepwise fashion is shown in Table 5.5. Absolute dew point and solar radiation were not significant in the stepwise addition of main effects to the base model, so they were removed. The significant main effects in the first step of our linear regression are shown in Table 5.6. These are the variables that qualified for the next step of interactions. Table 5.7 shows the main effects and all possible interactions between them. Two variables were removed from Table 5.7, these are the variables that are not significant in the second phase of our stepwise regression model and are shown in Table 5.8. The variables in the final model are shown in Table 5.9.

Table 5.5. Addition and removal of main effects in a stepwise fashion

Variable[1]	P-value	Process[2]	Criterion	
			AIC[3]	BIC[4]
Base model			5,022.3	5,020.7
Absolute ambient temperature[5]	0.0233	A	4,968.9	4,965.2
Absolute range of temperature[5]	0.0001	A	4,947.4	4,943.6
Monthly lag of wind speed[5]	0.0010	A	4,937.7	4,933.9
Absolute dew point	0.9406	NR	4,939.7	4,935.8
Absolute solar radiation	0.1755	NR	4,937.9	4,934

[1]Variable with 2,161 observations. Units are ˚C for ambient temperature, range of temperature and dew point, m/s for wind speed and W/m^2 for solar radiation.
[2]A = Addition of variable. NR on the same row variables were not retained.
[3]AIC = Akaike information criterion.
[4]BIC = Bayesian information criterion.
[5]Main effect variables that qualified for the next step of interactions.

Table 5.6. Main effects remaining in the model

Variable1	P-value	Criterion	
		AIC[2]	BIC[3]
Base model		5,022.3	5,020.7
Absolute ambient temperature	0.0233	4,968.9	4,965.2
Absolute Range of temperature	0.0001	4,947.4	4,943.6
Monthly lag of Wind speed	0.0010	4,937.7	4,933.9

[1]Variable with 2,161 observations. Units are ˚C for ambient temperature, range of temperature and dew point, m/s for wind speed and W/m^2 for solar radiation.
[2]AIC = Akaike information criterion.
[3]BIC = Bayesian information criterion.

Table 5.7. Significant main effects and all possible interactions between variables

Variable[1]	F-value	P-value
Base model		
Week of the year	29.39	0.0001
BW	8.41	0.0038
NEm intake		
Linear	2004.62	0.0001
Quadratic	348.75	0.0001
Absolute ambient temperature	4.92	0.0266
Absolute range of temperature	1.67	0.1961
Monthly lag of wind speed	1.14	0.2863
Absolute ambient temperature × Absolute range of temperature	1.22	0.2694
Absolute ambient temperature × Monthly lag of wind speed	3.75	0.0529
Absolute range of temperature × Monthly lag of wind speed	1.57	0.2104

[1]Variable with 2,161 observations. Units are Mcal/d for NEm intake, ˚C for ambient temperature, range of temperature and dew point, m/s for wind speed and W/m^2 for solar radiation. AIC = Akaike information criterion (4,936.2), BIC = Bayesian information criterion (4,932.2).

Table 5.8. Summary of variables removed from the model in the second stage. Cut off points used were P-value = 0.002 and F = 5.0

Variable[1]	F-value	P-value	Elimination step	Criteria	
				AIC[2]	BIC[3]
Base model					
Monthly lag of wind speed	1.14	0.2863	1	4,935.3	4,931.4
Absolute ambient temperature × Absolute range of temperature	0.10	0.7547	2	4,933.4	4,929.5

[1]Variable with 2,161 observations. Units are ˚C for ambient temperature and range of temperature and m/s for wind speed.
[2]AIC = Akaike information criterion
[3]BIC = Bayesian information criterion

Table 5.9. Final model with significant variables using REML estimation

Variable[1]	Estimates	SE[2]	F-value	P-value
Intercept	-1.8627	1.1679		0.1716
Base model				
Week of the year			30.13	0.0001
BW	0.001695	0.000554	9.38	0.0022
NEm intake				
Linear	0.8391	0.2054	1668.53	0.0001
Quadratic	-0.00597	0.000366	265.51	0.0001
Absolute ambient temperature	-0.2329	0.08381	7.72	0.0055
Absolute range of temperature	0.3236	0.06986	21.46	0.0001
Absolute ambient temperature × Monthly lag of wind speed	0.05970	0.02286	6.82	0.0091
Absolute range of temperature × Monthly lag of wind speed	-0.07236	0.01892	14.63	0.0001

[1] Variable with 2,161 observations. Units are ˚C for ambient temperature, range of temperature, m/s for wind speed, and Mcal/d for NEm intake. AIC = Akaike information criterion (5,001.2), BIC = Bayesian information criterion (4,999.7).
[2]SE= standard error

The main effect of ambient temperature shows that as ambient temperature increases, there is a reduction in DMI. For range of temperature, as range of temperature increases, DMI also increases.

The effect of the interaction between ambient temperature and wind speed on DMI of cows is shown in Figure 5.1. At low temperature, DMI decreases with increasing wind speed. On the other hand, at high (warmer) temperatures, DMI increases with increasing wind speed. The effect of temperature and wind speed has been reported previously (NRC, 1981). Wind speed is known to exacerbate the effect of cold temperatures. In hot weather, wind speed is known to increase the rate of evapotranspiration thereby reducing the effect of heat load on animals. In this study, we believe that the reduction in DMI observed as wind speed increases in cold weather could be because of the effect of wind chill which causes extreme acute cold stress in animals thereby affecting their DMI. Acute cold stress has been reported to cause changes in grazing cows (Adams, 1987). In this study, the cows were mostly fed forages and we believe the effect of cold stress on DMI by cows could be similar to what was reported by Adams (1987). Stanton

(1985) also reported that feed intake in cold stressed feedlot beef cattle does not increase in cold weather which is similar to what we observed.

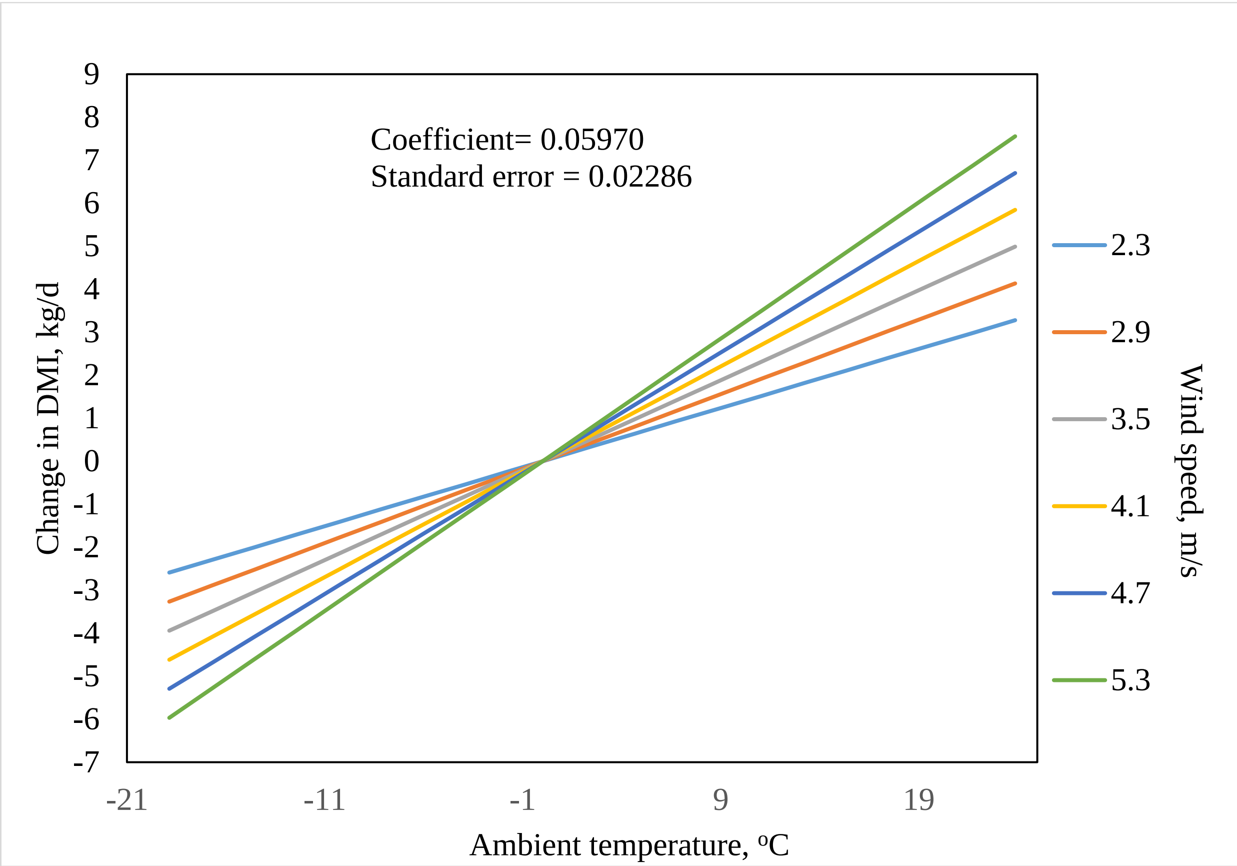

Figure 5.1. How ambient temperature interacted with wind speed to affect DMI of cows.

The effect of the interaction between range of temperature and wind speed on DMI of cows is shown in Figure 5.2. With increasing wind speed, DMI is higher at lower range of temperature and decreases as range of temperature increases. This shows that no matter the range of temperature, higher wind speed has a negative effect on DMI when temperature fluctuates. Fluctuation in temperature impacts the physiological mechanism of temperature regulation in cattle since generally, cattle adjust to changes in temperature gradually over time. Also, the temperature an animal has been previously exposed to affects its current basal metabolism as reported by NRC (1981). Therefore, abrupt high fluctuation in temperature could impact the metabolism of the animal which could result in changes in DMI since total heat production and external insulation are physiological changes that determine the rate of increase in energy when temperature is below the lower critical temperature in cold weather. In hot weather, lowering metabolic heat production to combat the heat stress when temperature is above the upper critical temperature would cause a reduction in DMI.

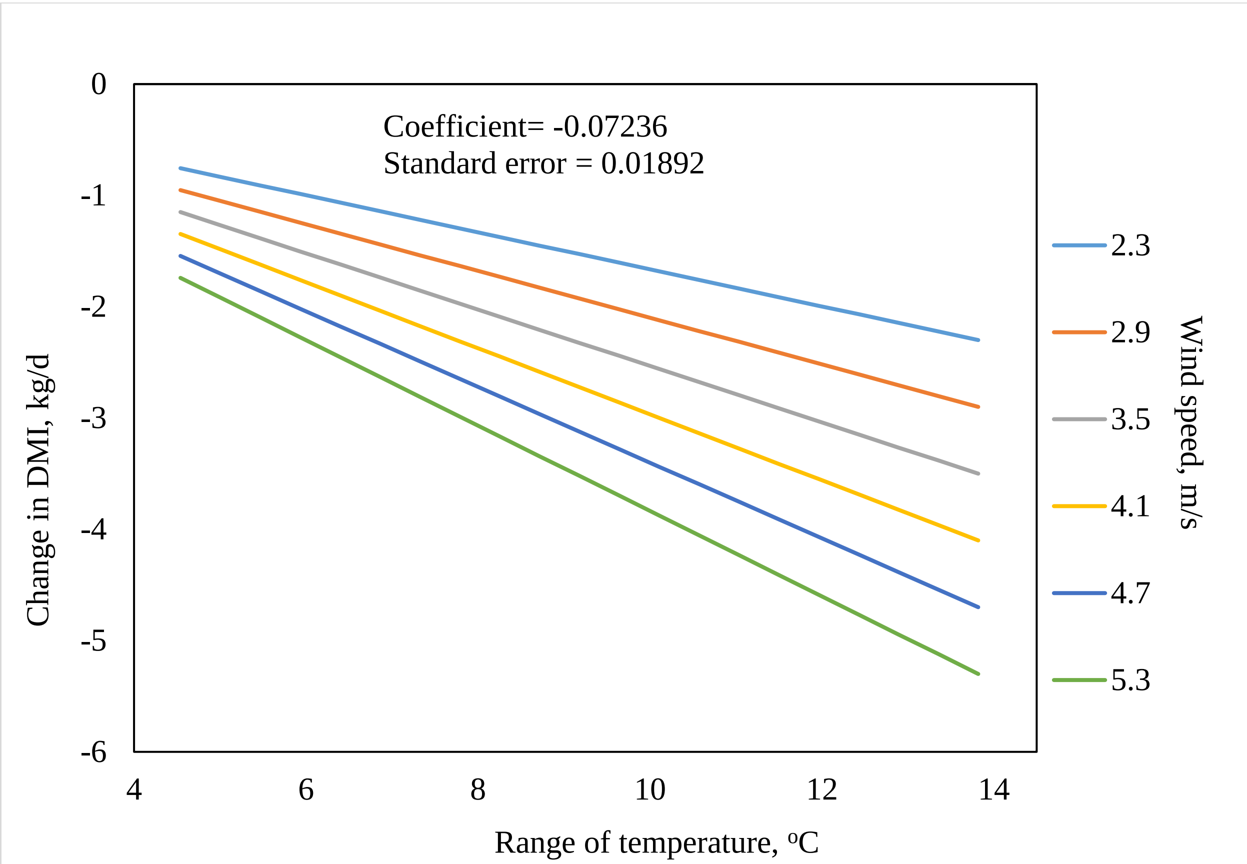

Figure 5.2. How range of temperature interacted with wind speed to affect DMI of cows.

5.6. Conclusion

Wind speed interacted with ambient temperature and range of temperature, and this accounted for additional variation in DMI of beef cows. This adds to our current understanding of the relationship between weather variables and DMI. Although the number of observations used in this study was adequate (2,161 cow-week observations), the result of this study should be interpreted with caution because of the low number of data points compared to some other models by the same authors.

5.7. Implication

This study will contribute to the improvement of the current DMI models most especially since the current ones are not a good fit for the Northern Great Plains. Our model adds range of temperature and the interactions between wind speed with ambient temperature and range of temperature to previous models of weather effects on DMI of beef cows.

5.8. Recommendations

The observations used in this study were only 2,161 cow-weeks observation. We recommend a study in cows with more observations to be able to capture variation better and make the model more robust.

5.9. Literature Cited

Adams, D. C. 1987. Influence of winter weather on range livestock. Pp. 23-29. *In proceedings of the Grazing Livestock Nutrition Conference, July, 1987, Jackson, WY*. Laramie: University of Wyoming.

Gunter, S. A. 2017. Predicting forage intake by grazing beef cattle. Florida Ruminant Nutrition Symposium, 28th Annual Meeting University of Florida, Institute of Food Agriculture Science, Gainesville, FL. Pages 125-136

Klein, S. I., P. L. Steichen, A. Islas, R. S. Goulart, T. C. Gilbery, M. L. Bauer, K. C. Swanson, and C. R. Dahlen. 2014. Effects of alternate-day feeding of dried distiller's grain plus solubles to forage-fed beef cows in mid- to late gestation. J. Anim. Sci. 2:2677–2685. DOI:10.2527/jas2013 7056

Montanholi, Y. R., K. C. Swanson, R. Palme, F. S. Schenkel, B. W. McBride, D. Lu, and S. P. Miller. 2010. Assessing feed efficiency in beef steers through feeding behavior, infrared thermography and glucocorticoids. Animal 4:692-701. DOI:10.1017/S1751731109991522

Mosher, K. M., S. Olorunkoya, N. Bhowmik, and K. A. Ringwall. 2021. Relationships among measures of efficiency with body weight, frame score, and body volume in lactating multiparous crossbred beef cattle. J. Anim. Sci. 99:47-48 DOI: https://doi.org/10.1093/jas/skab235.084

NRC. 1981. Effect of Environment on Nutrient requirements of Domestic Animals. National Academy Press, Washington, DC.

Stanton, T. L. 1995. Damage control strategies for cattle exposed to cold stress. Pp. 289-298 in symposium Proceedings:Intake by Feedlot Cattle, P-942, July 1995, F. N. Owens, ed. Stillwater: Oklahoma Agricultural Experiment Station.

Swanson, K. C., A. Islas, Z. E. Carlson, R. S. Goulart, T. C. Gilbery, and M. L. Bauer. 2014. Influence of dry-rolled corn processing and increasing dried corn distillers grains plus solubles inclusion for finishing cattle on growth performance and feeding behavior. J. Anim. Sci. 92:2531-2537. DOI:10.2527/jas.2013-7547

Tanner, A. R., M. L. Bauer, V. C. Kennedy, F. E. Keomanivong, J. D. Kirsch, L. P. Reynolds, G. L. Stokka, A. Rodas-Gonzalez, A. K. Ward, C. R. Dahlen, B. W. Neville, K. H. Ominski, K. A. Vonnahme, and K. C. Swanson. 2020. Influence of corn supplementation to beef cows during mid- to late gestation: maternal feed intake, body condition, plasma metabolites, and calf growth. Livestock Science 240. 104142.DOI:https://doi.org/10.1016/j.livsci.2020.104142

CHAPTER 6. †GENERAL CONCLUSIONS AND FUTURE DIRECTIONS

6.1. General Conclusions

Our studies show that weather variables interact and account for additional variation in DMI of beef cattle. In experiment 4, our results shows that weather variables account for additional variation in ADG. These studies have helped in better understanding the relationship between weather variables with DMI and ADG. This will improve the accuracy of DMI and ADG prediction models. Our studies also show that solar radiation has a large impact on how temperature affects intake, and the interaction of both and other weather variables influences the thermal balance of beef cattle.

These studies also validate the reports of NRC (1996, 2000; NASEM, 2016) explaining how the previous temperature that an animal has been exposed to affects their thermal balance. In these studies, we observed that the lags of weather variables have an impact on the current DMI and ADG of beef cattle, which explains that biological responses to weather is gradual over time.

6.2. Future Directions

The results from these studies have shown that weather variables and their interactions are more complex than we previously understood because animals also have a complex mechanism of thermal control. Conducting more studies like this will improve our understanding of the complexity of weather and its interaction on animal's responses. More data from various locations will help in increasing the robustness of the current models. For the cow intake study, the observations used were few and it is recommended to conduct more studies with more numbers of observations.

APPENDIX. SUPPLEMENTAL TABLES

Table A.1. AIC and BIC values of various models examining solar radiation as a predictor variable for DMI in beef steers

Variable[1]	AIC[2]	BIC[3]
Base model only	45,151*	45,160*
Two-week lag of ambient temperature + base model	45,017†	45,038†
Monthly lag of solar radiation + base model	45,058†	45,080†
Two-week lag of ambient temperature + Monthly lag of solar radiation + base model	45,018†	45,040†
Two-week lag of ambient temperature + Monthly lag of solar radiation and their interaction + base model	45,013†	45,035†
Interaction between two-week lag of ambient temperature and monthly lag of solar radiation + base model [4]	45,011†	45,032†
Best model using restricted maximum likelihood estimation method	45,113*	45,121*

[1] Variable with 13,895 observations. Units are °C for temperature and W/m^2 for solar radiation,
[2]AIC = Akaike information criterion
[3]BIC = Bayesian information criterion
[4] Best model
†Maximum likelihood estimation method was used
*Restricted maximum likelihood estimation method was used

Table A.2. AIC and BIC values of various models examining the relationship between weather variables and DMI in beef steers

Variable[1]	AIC[2]	BIC[3]
Base model	45,151*	45,160*
Two-week lag of ambient temperature + base model	45,017†	45,038†
Two-week lag of range of temperature + variables from previous line	44,944†	44,965†
Two-week lag of solar radiation + variables from previous line	44,885†	44,908†
Two-week lag of ambient temperature × Two-week lag of range of temperature + variables from previous line	44,871†	44,894†
Two-week lag of ambient temperature × Monthly lag of wind + variables from previous line	44,833†	44,856†
Two-week lag of ambient temperature × Absolute dew point + variables from previous line	44,835†	44,858†
Two-week lag of ambient temperature × Two-week lag of solar radiation + variables from previous line	44,794†	44,817†
Two-week lag of range of temperature × Absolute dew point + variables from previous line	44,751†	44,775†
Monthly lag of wind speed × Two-week lag of solar radiation + variables from previous line[4]	44,731†	44,755†
Best model using restricted maximum likelihood estimation method	44,912*	44920*

[1] Variable with 13,895 observations. Units are °C for ambient temperature, range of temperature and dew point, m/s for wind speed and W/m^2 for solar radiation.
[2]AIC = Akaike information criterion
[3]BIC = Bayesian information criterion
[4] Best model
†Maximum likelihood estimation method was used
*Restricted maximum likelihood estimation method was used

Table A.3. AIC and BIC values of various models that examined the influence of weather variables on average daily gain of beef steers

Variable[1]	AIC[2]	BIC[3]
Base model	18,609*	18,618*
Monthly lag of range of temperature + base model	18,413†	18,434†
Absolute dew point + variables from previous line	18,369†	18,391†
Two-week lag of ambient temperature + variables from previous line	18,291†	18,313†
Monthly lag of wind speed + variables from previous line	18,273†	18,295†
Monthly lag of solar radiation × Monthly lag of range of temperature + variables from previous line	18,147†	18,170†
Monthly lag of solar radiation × Absolute dew point + variables from previous line	18,091†	18,114†
Monthly lag of solar radiation × Two-week lag of ambient temperature + variables from previous line	18,054†	18,077†
Monthly lag of solar radiation × Monthly lag of wind speed + variables from previous line	17,926†	17,949†
Monthly lag of range of temperature × Absolute dew point + variables from previous line	17,848†	17,872
Monthly lag of range of temperature × Monthly lag of wind speed + variables from previous line	17,842†	17,865†
Absolute dew point × Two-week lag of ambient temperature + variables from previous line[4]	17,764†	17,788†
Best model using restricted maximum likelihood estimation method	18,037*	18,046*

[1] Variable with 13,739 observations. Units are °C for ambient temperature, range of temperature and dew point, m/s for wind speed and W/m^2 for solar radiation.
[2]AIC = Akaike information criterion
[3]BIC = Bayesian information criterion
[4] Best model
†Maximum likelihood estimation method was used
*Restricted maximum likelihood estimation method was used.

Table A.4. AIC and BIC values of various models that examined how weather variables influenced DMI of beef cows

Variable[1]	AIC[2]	BIC[3]
Base model	5,022.3*	5,020.7*
Absolute ambient temperature + base model	4,968.9†	4,965.2†
Absolute range of temperature + variables from previous line	4,947.4†	4,943.6†
Absolute ambient temperature × Monthly lag of wind speed + variables from previous line	4,941.6†	4,937.8†
Absolute range of temperature × Monthly lag of wind speed + variables from previous line[4]	4,933.4†	4929.5†
Best model using restricted maximum likelihood estimation method	5001.2*	4999.7*

[1] Variable with 2,161 observations. Units are °C for ambient temperature, range of temperature, m/s for wind speed, and Mcal/d for NEm intake
[2]AIC = Akaike information criterion
[3]BIC = Bayesian information criterion
[4] Best model
†Maximum likelihood estimation method was used
*Restricted maximum likelihood estimation method was used.