EVALUATING AND DEVELOPING WATER INTAKE PREDICTION EQUATIONS FOR GROWING AND FINISHING FEEDLOT STEERS

By

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EVALUATING AND DEVELOPING WATER

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Title of Study: EVALUATING AND DEVELOPING WATER INTAKE PREDICTION EQUATIONS FOR GROWING AND FINISHING FEEDLOT STEERS

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Abstract: A study was conducted to evaluate 8 published water intake (**WI, L/d**) equations. Individual WI and DMI were collected on growing (**GRW**; *n* = 243) and finishing (**FIN**; *n* = 46) feedlot steers using an Insentec Roughage Intake Control System. Published equations were evaluated by predicting WI using 42 d DMI, BW, and weather records. Equation 5 performed with greatest accuracy (mean bias = -1.33; linear bias = -0.14) and precision (R^2 = 0.41; RMSE = 6.81) for GRW. Equations 2a (R^2 = 0.34; RMSE = 5.46; mean bias = 3.42; linear bias = 0.128) and 2b (R^2 = 0.36; RMSE = 5.37; mean bias = 3.44; linear bias = -0.015) performed with greatest accuracy and precision for FIN. A second study was conducted to examine the impact of solar radiation (**SR**) and DMI on WI and water intake as a percent of body weight (**WI%BW**) prediction equations. Four WI and 4 WI%BW finishing equations were developed to include all variables (**OVRL**), include DMI without SR (**DMIO**), include SR without DMI (**SRO**), or exclude both DMI and SR (**SIMP**). Equations were evaluated using an independent dataset (*n* = 27). The OVRL equations resulted in most favorable regression statistics during development. The DMIO WI (R^2 = 0.889; RMSE = 1.220; *F*-ratio = 74.27) and WI%BW (R^2 = 0.890; RMSE = 0.255; intercept = 1.960) models produced more favorable regression statistics compared to SRO and SIMP. The WI%BW equations usually had lower prediction errors and better model fit than WI. During evaluation, DMIO (R^2 = 0.67; RSME = 4.87) and SIMP (R^2 = 0.64; RMSE = 5.08) WI equations performed with greatest precision. The OVRL WI (mean bias = 2.40; linear bias = -0.09) equation performed with greatest accuracy. All WI%BW equations resulted in similar levels of precision (R^2 = 0.57 to 0.59; RMSE = 1.16 to 1.19) except DMIO. The OVRL (mean bias = 0.69; linear bias = -0.05) and DMIO (mean bias = 1.96; linear bias = 0.28) WI%BW equations performed with greatest accuracy. These results indicate that including DMI and SR or only DMI resulted in optimal equation performance.

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CHAPTER I

REVIEW OF LITERATURE

GLOBAL WATER CRISIS

Livestock require continuous access to water to maximize production. However, water resources have become scare worldwide which limits productivity. Water resources have become scarce worldwide due to climate change, and water scarcity is especially concerning for emerging economies that rely on rain to provide access to water. In 2018, residents in Cape Town, South Africa barely escaped what was referred to as “Day Zero” meaning that the city would run out of access to water after suffering years of drought (LaVanchy et al., 2019). The city implemented a variety of water policies such as limiting the amount of water allocated per person to 50 L/d to reduce citywide water use, but residents must remain cautious to prevent Day Zero from occurring in upcoming years (LaVanchy et al., 2019). Additionally, water resources are being depleted at an unsustainable rate. The Ogallala Aquifer, which spans across the United States of America Great Plains, is being drained faster than its recharge rate due to pumping for crop irrigation in this region (Basso et al., 2013). In addition, Lake Victoria, which spans across the borders of Kenya, Uganda, and Tanzania, has been shrinking in size over the years (USDA, 2005). Thus, water use continues to be a major concern for farmers around the world.

In many countries, there are distinct rainy and dry seasons that require pastoralists to participate in seasonal migrations with their livestock in search of water sources and forage availability (Majekodunmi et al., 2014). However, changes in climate, such as increased prevalence of drought, delayed rains, and rising temperatures, contribute to food insecurity in already vulnerable regions (Gregory et al., 2005). Water scarcity has been identified as one of the top reasons for seasonal migrations for pastoralists (Suleiman et al., 2015). Farmers need to relocate their livestock to water sources during the dry and wet seasons due to limited access to these sources that are diverted for crop production (Majekodunmi et al., 2014). Additionally, rainfall plays an important role in livestock water consumption. During the rainy season, cattle free water consumption has been found to be lower than the dry season which is partly due to an increase in water consumed from forages (Duguma et al., 2012).

As world population estimates for 2050 approach 10 billion people (UN, 2017), water resource use will become a major concern for livestock producers. Water requirements across species vary with cattle consuming more water than sheep and goats (Coppock et al., 1988; Duguma et al., 2012). Thus, understanding cattle water requirements is of utmost importance for farmers to sustainably produce nutritious beef and dairy products.

THE NUTRITIONAL VALUE OF WATER

Water is an essential nutrient for livestock production as it provides a variety of physiological functions (NASEM, 2016). Water regulates body temperature, serves as a solvent for vitamins, minerals, and other molecules, and is involved in metabolism, reproduction, and digestion processes including hydrolysis of fats, proteins, and carbohydrates (NASEM, 2016). Thus, water requirements for cattle is defined as the amount of water needed to perform all metabolic, digestive, and physiological processes. Cattle water requirements can be achieved through a combination of free water consumption, water from feed, and metabolic water production (NASEM, 2016). Water obtained from feed or metabolic production contribute to a smaller proportion of the animal's total water consumption; the majority of which is attributed to free water consumption (Winchester and Morris, 1956; NASEM, 2016). For instance, one study explained that 78% of total water consumption was ingested as free drinking water for dry and lactating cows (Holter and Urban, 1992). Additionally, 1 kg of protein, fat, and carbohydrates only produces 0.5, 1.2, and 0.5 L of water during oxidation (Church, 1988).

CATTLE WATER REQUIREMENTS IN THE UNITED STATES

It has been estimated that it takes 3,682 L of water to produce 1 kg of boneless beef in the United States (Beckett and Oltjen, 1993). In addition, the beef cattle industry has been estimated to consume 25,325,109 X 10^6 L of water per year, which includes free drinking water and water consumed from feed by cattle in each sector of the industry, water used for pasture and crop irrigation, and water used during carcass processing (Beckett and Oltjen, 1993). Of this figure, 153,288 X 10^6 and 8,695,582 X 10^6 L of water were consumed as free drinking water or from feed, respectively, during the feedlot phase (Beckett and Oltjen, 1993). Based on those estimates, feedlot cattle accounted for ~35% of U.S. beef cattle water consumption.

A compilation of beef and dairy cattle daily water intakes (WI) throughout the United States from 10 selected publications are reported in Table 1.1 and represent only free drinking WI. Average, minimum, and maximum water consumption across the U.S. were 44.6, 24.6, and 89.2 L/d. This large range in WI emphasizes the variability across classes of animals which makes estimating free water consumption difficult. Additionally, only 3 of the selected studies reported

WI on an individual animal basis; whereas, other studies tended to measure WI on a pen basis using water meters. Thus, there is likely substantial variation in WI among individual animals that are not represented in these estimates.

FACTORS AFFECTING WATER INTAKE

An animal's daily water intake (WI) is greatly impacted by multiple factors including diet (i.e. dry matter intake), environment, and physiological state (i.e. body weight and milk production). As such, it is impossible to predict an individual animal's water consumption but estimating consumption for a large group of animals or an entire herd can be accomplished more reliably (Winchester and Morris, 1956).

Dietary influences

Diet characteristics such as dry matter intake (DMI), dietary salt levels, ration type (concentrate vs. forages), protein levels, and dry matter content can vastly change water intakes for cattle. Out of these, DMI is most often included in models predicting cattle water intake, but other dietary components must be considered to make appropriate conclusions on the relationship between DMI and WI. Additionally, some studies have found differences among WI for cattle under different bunk management scenarios.

Dry matter intake. Dry matter intake has been found to influence WI, but this influence has been inconsistent throughout the literature. Researchers have noted a positive relationship between DMI and WI, meaning that an animal consumes more water as DMI increases, for finishing cattle (Hicks et al., 1988; Arias and Mader, 2011), growing cattle (Meyer et al., 2006;

Ahlberg et al., 2018; Zanetti et al., 2019), and dry (Holter and Urban, 1992) and lactating (Little and Shaw, 1978; Murphy et al., 1983; Holter and Urban, 1992; Cardot et al., 2008) dairy cows. Feed intake was also found to be positively correlated with WI ($P < 0.001$) for growing cattle (Brew et al., 2011). However, these results can be misleading as DMI tends to increase during cooler weather and decrease in warmer weather while WI usually has the opposite trend (Sexson et al., 2012) to account for the impact of metabolic heat production and environmental heat loads on maintaining thermal homeostasis (Beade and Collier, 1986). The increase in WI associated with heat stress also negatively impacts feed intake due to increased gut fill (Beade and Collier, 1986). Sexson et al. (2012) reported a positive relationship between WI and DMI in a univariate analysis with WI increasing by 0.349 L/d for each 1 kg increase in DMI, but DMI was not statistically significant in the overall prediction of WI for yearling feedlot steers fed a finishing ration.

In addition, DMI influences WI to varying extents for growing and finishing cattle. For instance, Ahlberg et al. (2018) found that DMI explained 5 to 29% of the variation in WI for growing steers during multivariate analyses and DMI was an important variable for predicting WI in all models. Meyer et al. (2006) noted that DMI accounted for 10.4% of the variation in WI for growing bulls. Arias and Mader (2011) noted that DMI was not a major predictor of WI for finishing cattle but explained 2% of the variation in WI in their overall models. Dry matter intake was a primary driver of WI for finishing cattle (partial $R^2 = 0.1501$) in the Hicks et al. (1988) study, while Zanetti et al. (2019) stated that WI increased by 0.489 L/d for every kg/d of DMI which was the largest coefficient out of all predictor variables included in the model.

Furthermore, dry matter intakes are not always available to producers, so these must be estimated. Thus, the relationship between DMI and WI is complex and the inclusion of DMI in WI prediction equations needs to be further evaluated.

Diet composition. Protein, salt, dry matter content, roughage, and concentrate levels of the diet influence cattle water requirements (Hicks et al., 1988; Holter and Urban, 1992; Rouda et al., 1994; Meyer et al., 2006; Cardot et al., 2008; NASEM, 2016). The relationship between WI and dry matter content or moisture content of the diet has been briefly explored and primarily evaluated for dairy cattle. One study found that the dry matter content of the diet accounted for 5.3% of the variation in WI and increased WI by 0.89 L/d for every 1% increase in dry matter content for lactating dairy cows (Cardot et al., 2008). Holter and Urban (1992) evaluated the impact of dry matter percentage of the diet on total and free water intake for dry and lactating Holstein cows and found that it was correlated with free WI for dry (r = 0.45) and lactating (r = 0.40) cows. When only dry matter content was included in the model, linear and quadratic forms accounted for only 19% of the variation in free WI for lactating cows. The authors also found that free WI increased for dry cows when moisture content of the diet changed from 70% to 40%. Little and Shaw (1978) noted that dry matter content of the diet was not correlated with WI for dairy cows. Meyer et al. (2006) found that the dry matter percentage of the roughage increased model R^2 by 0.021 and increased WI by 0.248 L/d for growing dairy bulls. Winchester and Morris (1956) mentioned that the water consumed from feed on rations that are primarily composed of hay and grain is less than 0.3 gallons per day; thus, WI from feed for cattle consuming these diets is negligible when examining total WI.

Increasing protein levels in the diet increases cattle water requirements (NASEM, 2016). A positive correlation was reported between dietary crude protein (% DM) and free WI (r = 0.63) and total WI (0.51; $P < 0.05$) for dry cows, and when crude protein ranged from 12 to 13 % DM, WI increased by 1 L/d for every 1 % DM increase in crude protein (Holter and Urban, 1992). However, Rouda et al. (1994) found that grazing crossbred lactating and nonlactating cows fed a cottonseed meal pelleted supplement (CP = 41%) consumed less water than those that were not offered the supplement.

Hicks et al. (1988) examined the impacts of feeding 0, 0.25, or 0.50 % dietary salt levels on daily finishing steer WI. The authors noted that salt levels did not greatly influence WI among the 3 treatment levels as WI was 10.18, 8.98, and 9.33 gal/d for steers consuming diets with 0, 0.25, and 0.5 % added salt, respectively. However, Hicks et al. (1988) developed a WI prediction equation using data across all treatment levels and found that WI decreased by 1.174 gal/d for every 1% increase in salt level.

Since finishing feedlot diets are higher in concentrate and dry matter content of the diet, it is expected that cattle consuming a finishing diet would have greater water requirements compared to those consuming a growing diet if all other factors influencing WI remained equal.

Bunk management. Few studies have noted the relationship between WI and feeding management strategies. Ahlberg et al. (2018) examined the impact of WI for growing steers fed according to *ad libitum* or slick bunk strategies and found that steers fed ad libitum drank 0.87% of body weight more water than the slick bunk groups. However, the factors influencing WI changed depending on feeding strategy. The major factors predicting WI for *ad libitum* fed steers were average daily temperature (TAVG) and metabolic body weight (partial R^2 = 0.23 and 0.11; respectively); whereas, TAVG and DMI (partial R^2 = 0.19 and 0.15; respectively) were the major drivers of WI for slick bunk fed steers. In addition, Mader and Davis (2004) collected WI on feedlot steers fed *ad libitum*, fed at 1600 with bunks managed to be empty the following morning (bunk management; BKMGT) or were limit fed at1600 (LIMFD), which was defined as providing 85% of projected *ad libitum* feed. Steers fed *ad libitum* consumed more water than LIMFD steers. The results from these 2 studies emphasize the importance of DMI as a driving factor of WI for feedlot steers.

Environment

Environmental factors, including temperature, solar radiation, wind speed, relative humidity, temperature-humidity index, and precipitation, influence the amount of water an animal consumes, and patterns in water consumption due to seasonality have been described.

Season. Seasonal variations in WI have been noted with cattle consuming more water throughout the summer than the winter (Hoffman and Self, 1972; Holter and Urban, 1992; Arias and Mader, 2011; Ahlberg et al., 2018). One study noted that cattle consumed 87.3% more water in the summer than in the winter (Arias and Mader, 2011). The seasonal differences can be attributed to the impact of higher summer environmental variables on increasing an animal's thermal heat load. A variety of environmental factors contribute to heat stress in ruminants including temperature, solar radiation, relative humidity, and wind speed (Morrison, 1983), and the relationship between these factors and WI is complex. As temperatures increase, cattle begin to lose more water through evaporative cooling to regulate body temperature requiring animals to consume more water (Berman, 2006). Alternatively, as relative humidity increases, water losses from evaporative cooling decrease (Ragsdale et al., 1953) which reduces the animal's water requirement. Shade structures can alter an animal's environment to reduce the impacts of heat stress. However, feedlot cattle are rarely provided with access to shade leading to increased exposure to solar radiation. These conditions lead to increased thermal heat load for cattle in a feedlot, especially during the summer, which would increase cattle water requirements. Hoffman and Self (1972) found that shelter had a significant impact on finishing yearling steer water consumption in a feedlot in Iowa with cattle consuming less water in the summer when shelter was available. These authors found that shelter did not significantly impact WI during the winter. The authors explained that the increase in WI for cattle without access to shelter in the summer could be due the effects of solar radiation on increasing skin surface evaporation rates.

Ambient temperature. The influence of temperature on WI has been extensively examined throughout the literature. As a result, various temperature measures have been found to impact WI. In general, numerous studies have found that WI tends to increase with higher temperatures (Ittner et al., 1951; Harbin et al., 1958; Murphy et al., 1983; Hicks et al., 1988; Ali et al., 1994; Meyer et al., 2006; Cardot et al., 2008; Arias and Mader, 2011; Sexson et al., 2012; Wichramasinghe et al., 2019; Zanetti et al., 2019). Hoffman and Self (1972) found that temperature was highly correlated with finishing steer daily WI in the summer with (r = 0.93) and without (r = 0.94) access to shelter. Water intake was also highly correlated to temperature for cattle finished in the winter with access to shelter (r = 0.99). In addition, the authors noted that cattle consumed the majority of their daily WI during the hottest periods of the day (9 am to 9pm).

Average, minimum, and maximum daily temperatures are the most commonly associated temperature measures found to influence cattle WI. In multivariate analyses, maximum daily temperature has been described as an important predictor that increases WI (Hicks et al., 1988; Zanetti et al, 2019). Specifically, Hicks et al. (1988) reported that TMAX accounted for 49.96% of variation in finishing steer WI. Ahlberg et al. (2018) found that average daily temperature (TAVG) was an important predictor variable across seasons and feeding management strategies and TAVG accounted for 3.3 to 23 % of the variation in growing steer WI in final prediction models. Minimum temperature (TMIN) was the most important predictor of WI (partial R^2 = 0.56) across summer and winter datasets for finishing cattle (Arias and Mader, 2011). Murphy et al. (1983) noted that WI increased by 1.2 L/d for every 1 °C increase in TMIN and TMIN accounted for 15.4 % of the variation in WI for lactating Holstein cows. Cardot et al. (2008) also included TMIN in their final WI prediction model for lactating Holstein cows but TMIN only accounted for 1.6 % of the variation in WI and increased WI by 0.57 L/d for every 1 °C increase in TMIN.

However, other studies noted that temperature did not impact WI (Little and Shaw, 1978; Brew et al., 2011). One possible reason for some of the inconsistencies in temperature associations with WI is that there may be temperature thresholds that result in water consumption patterns. Water intake was found to decrease below a minimum daily temperature of 15 °C but was constant above this temperature up to 25°C, and previous day maximum temperature increased steer WI by 2 to 3 L/d when temperatures ranged from 25 to 45 °C (Sexson et al., 2012). In addition, no correlations between WI and a variety of temperature measures were found for grazing cattle until average daily temperature reached above 30 °C (r = - 0.11; *P* = 0.02; Rouda et al., 1994). Appuhamy et al. (2016) noted a positive, linear association between WI and mean ambient temperature for lactating dairy cows, but only between 8 to 32.5 °C. Lastly, Winchester and Morris (1956) described a curvilinear effect of ambient temperature on WI in gallons per pound of DM consumed. Water intakes for *Bos indicus* and *Bos taurus* cattle were constant up to 40 °F and increased at an increasing rate above this value. These studies support that cattle must increase WI to make up for water lost by heat dissipation mechanisms during instances of high ambient temperatures.

Relative humidity. High relative humidity can decrease an animal's ability to dissipate heat through evaporative cooling since the air is already highly saturated with water vapor which leads to decreased water requirements (Ragsdale et al., 1953). Additionally, water lost through respiration decreases with increasing air temperature and relative humidity up to 45% (Berman, 2006). Thus, it is expected that as relative humidity increases WI decreases. An inverse relationship between WI and humidity has been described in various studies (Ragsdale et al., 1953; Ali et al., 1994; Arias and Mader, 2011; Ahlberg et al., 2018; Zanetti et al., 2019). Sexson et al. (2012) noted a negative relationship between WI and all relative humidity measures (linear and quadratic measures of average, minimum, and maximum humidity) in a univariate analysis but described both positive and negative relationships in a multivariate model. These authors found that WI increased by nearly 2 L/d for each steer from 20 to 50% average daily humidity (HAVG); whereas, there was only a 1 L decrease in daily steer WI for every 10% increase in humidity above 50%. The authors also described a positive linear effect of low humidity and a negative quadratic effect of high humidity on WI. Steer WI increased by 0.038 L/d for every 1% increase in low humidity. For every 10% increase in high humidity between 30 to 100%, daily steer WI decreased by 0.5 L. Lastly, Arias and Mader (2011) explained that relative humidity was a predictor of WI for finishing cattle during the winter but was not an important predictor in the summer or combined season models. Thus, relative humidity has been shown to have an important influence on cattle WI, but the relationship between WI and humidity may change depending on season and the specific humidity measure examined.

Temperature-humidity index. Temperature-humidity index (THI), which is calculated using the following equation: THI = (0.8 X Ambient temperature) + [(relative humidity/100) (ambient temperature - 14.4)] + 46.4 (Arias and Mader, 2011), has only been evaluated as a potential WI predictor variable in the last decade. Possible reasons for THI being uncommonly used is that humidity and various temperature measures were already included in the WI prediction model and THI was strongly correlated to those variables. For instance, Arias and Mader (2011) found that THI was highly correlated to finishing cattle WI (R^2 = 0.57) among seasons in a univariate analysis, but THI had multicollinearity with minimum (TMIN) and maximum (TMAX) ambient temperatures during equation development. Thus, the authors developed 2 overall WI models. The first WI model included TMIN but did not contain THI. The second WI model included THI but did not include TMIN or TMAX. Arias and Mader (2011) noted that THI was among one of the most important WI predictor variables for finishing cattle. Similarly, Sexson et al. (2012) evaluated the relationship between WI and THI in a univariate analysis and noted a positive relationship. As THI increased by 1 °C, WI increased by 0.756 L/d for finishing yearling feedlot steers. Temperature-humidity index was not a predictor of WI in the final prediction model, but various relative humidity and temperature measures remained in the model. In addition, Ahlberg et al. (2018) examined THI as a possible predictor variable for growing feedlot steers but found that THI was not an important predictor. Average relative humidity and ambient temperature remained in their final models. Thus, it may not be necessary to include THI in WI prediction models if temperature and humidity measures are better predictors of cattle WI. However, temperature and humidity measures could be excluded from WI models if THI is a better predictor of cattle WI.

Solar radiation. Solar radiation (SR) tends to have a positive relationship with WI (Arias and Mader, 2011; Ahlberg et al., 2018), but also had a negative influence on WI for growing steers fed during the summer (Ahlberg et al., 2018). Solar radiation explained 6 to 7% of the variation in WI for finishing cattle (Arias and Mader, 2011); whereas, SR explained less than 1% of WI for growing steers (Ahlberg et al., 2018). The small percentage of variation in WI explained by SR in the Ahlberg et al. (2018) was attributed to cattle having access to shade that could have reduced the impact of SR. Brosh et al. (1998) noted that growing Hereford heifers consuming a diet with 7.2 MJ/kg DM metabolizable energy (ME) had higher WI than those consuming a diet with 10.6 MJ/kg DM ME but there was an interaction between exposure to solar radiation (either with or without 11.5m^2 of shade availability for each animal) and diet type. These results suggest that both metabolic and environmental heat load play an important role in regulating water requirements.

Wind speed. The relationship between wind speed and WI has been explored. Sexson et al. (2012) described a positive relationship between average daily wind speed and WI in a univariate analysis but noted a negative relationship in the multivariate analysis. In the prediction model, a 1 km/h increase in average daily wind speed lowered daily steer WI by 0.055 L. Similarly, Ahlberg et al. (2018) found a negative relationship between WI and average daily wind speed for growing steers fed *ad libitum* and slick bunk during the summer and winter in multivariate analyses. Arias and Mader (2011) reported that wind speed was among one of the most important drivers of finishing cattle WI during the winter. Lastly, Brody et al. (1954) explained that wind speed aids in cooling cattle through convection, but it would not be expected to have a high influence on WI for cattle exposed to moderate temperatures. In addition, the authors noted that WI for lactating dairy cattle was not substantially influenced by low (0.5 mph) or high (8 – 9 mph) wind speeds.

Precipitation. Rainfall has been found to have a negative relationship with WI in few studies. Hicks et al. (1988) found that WI decreased by 2.597 gallons per day for every inch of weekly average precipitation, but precipitation was not a primary driver of finishing cattle WI. On the contrary, precipitation was found to be an important predictor of WI for cattle finished during the winter (partial R^2 = 0.05) and WI decreased by less than 0.50 L/d for every 1 cm/d increase in precipitation (Arias and Mader, 2011). Cardot et al. (2008) found that WI decreased by 0.30 L/d for every 1 mm/d increase in rainfall. Additionally, high rainfall leads to increased moisture content of the air. So, the negative relationship between precipitation and WI may be confounded with the influence of relative humidity on WI.

Physiological state

Cattle with different physiological states including body weight, sex, stage of production, and breed have varying WI. As mentioned preciously, it is well described that *Bos indicus* cattle consume less water than *Bos taurus* (Ittner et al., 1951; Winchester and Morris, 1956; Brew et al., 2011). One study examined the impact of breed, sex**,** and body weight on water intake for growing beef calves (Brew et al., 2011). Brew et al. (2011) used a GrowSafe™ system to measure individual water intake of 12 different breeds and crossbred steers, heifers, and bull calves. The authors found that Charolais X Angus cattle had highest WI (L/d or L/kg MBW) while the Charolais X Romosinuano cattle had the lowest WI (L/d), which indicates that breed differences can influence WI in beef cattle. Additionally, WI (L/kg MBW) was not different between steers, bulls, and heifers.

Stage of production such as lactating, pregnant, grazing, growing, or finishing cattle impact water consumption. Lactating cows consume more water than nonlactating cows (Rouda et al., 1994; Holter and Urban, 1992; Harbin et al., 1958) because milk production has been found to increase WI by 0.87 (Winchester and Morris, 1956) to 0.90 (Murphy et al., 1983) L/d per kg of milk. Winchester and Morris (1956) also noted that pregnancy increases WI particularly in the last 2 to 3 months of gestation. Growing cattle were described to have increased WI which was primarily a factor of the increased DMI during this stage, and the WI for grazing cattle is driven by the moisture content of the forages grazed (Winchester and Morris, 1956).

Body weight measures such as live animal body weight (BW), metabolic body weight (MBW), and shrunk body weight (SBW) influence WI differently. Sexson et al. (2012) found that metabolic body weight (MBW) and body weight (BW) had positive and negative roles in predicting WI for feedlot cattle, respectively, in a multivariate analysis. These authors described a quadratic relationship between BW and WI with intakes increasing in yearling feedlot steers weighing 300 to approximately 500 kg but decreasing beyond this weight. The authors explained that this may due to a decrease in water and protein in weight gain coupled with an increase in fat deposition as steers surpass 500 kg. Meyer et al. (2006) noted a positive relationship between WI and BW with WI increasing by 0.014 L/d for every kg increase in BW, but BW only account for 1.5% of the variation in WI. Ahlberg et al. (2018) found that MBW explained 1 to 11% of the variation in WI in their multivariate models and increased WI by 0.11 to 0.22 L/d for every kg increase in MBW for all models except for the ad libitum model which showed that WI decreased by 0.009 L/d per kg increase in MBW. Similarly, Zanetti et al. (2019) reported that WI increased by 0.190 L/d for every kg increase in MBW. Alternatively, Little and Shaw (1978) did not find a relationship between WI and BW. Thus, the relationship between WI and BW is not straightforward but tends to have an impact on WI.

MEASURING WATER INTAKE

Cattle WI have been commonly measured using pen water meters for a group of cattle (Sexson et al., 2012; Arias and Mader, 2011; Mader and Davis, 2004; Hicks et al., 1988; Hoffman and Self, 1972) or for cattle housed individually (Harbin et al., 1958; Little and Shaw, 1978; Brosh et al., 1998; Wickramasinghe et al., 2019), and WI are rarely measured on an individual animal basis (Brew et al., 2011; Ahlberg et al., 2018; Zanetti et al., 2019). However, WI is variable among individual animals (SD = 8.56 L/d, Brew et al., 2011; SD = 4.84 to 13.07 L/d, Ahlberg et al., 2018; SD = 6.49 L/d; Zanetti et al., 2019) and behavior can change when cattle are placed into individual pens compared to group housing (Babu et al., 2004). New technologies such as the Insentec Roughage Intake Control (**RIC**) feeding system allows researchers to measure WI on an individual basis with cattle housed in pens. The RIC system scans electronic identification (**eID**) ear tags as each animal enters the feed or water bunks and measures the amount consumed at each bunk visit, which are totaled at the end of the day to obtain individual daily feed and water intakes. Thus, the RIC system simulates water intake behavior in a traditional feedlot setting more effectively than collecting WI on animals housed individually and allows for more accurate daily WI measurements for pens of cattle.

CURRENT FEEDLOT WATER INTAKE PREDICTION EQUATIONS

Numerous WI prediction equations have been developed for growing (Ahlberg et al., 2018; NASEM, 2016) and finishing (Hicks et al., 1988; Arias and Mader, 2011; Sexson et al., 2012; NASEM, 2016) feedlot cattle in the United States. Since data for these equations were collected over varying seasons and the authors examined the impact of a multitude of predictor variables on WI, different combinations of animal and environmental variables remained in the final prediction models.

Hicks et al. (1988) developed a WI prediction equation after collecting pen level WI on 47 crossbred yearling steers fed a high concentrate finishing diet throughout the summer (June to September) in Oklahoma. Water intake data was collected over 92 d using water meters on tanks shared between pens, which had 7 to 8 steers per pen. Each set of 15 to 16 steers that shared water tanks were assigned to treatments of 0, 0.25, or 0.50% added dietary salt levels. The authors developed a WI prediction equation including WI data from all 3 treatments based on average weekly data. The final model (R^2 = 0.7361) included maximum temperature (partial R^2 = 0.4996), dry matter intake (partial R^2 = 0.1501), precipitation (partial R^2 = 0.0527), and dietary salt level (partial R^2 = 0.0337). Maximum temperature was the most important factor influencing WI while DMI was the second most influential variable for predicting finishing steer WI in this equation.

Arias and Mader (2011) evaluated daily WI for finishing steers (*n* = 642) and heifers (*n* = 636) over the summer and winter in Nebraska. In univariate analyses, the authors found that the variables with the greatest impact on WI were different within season. Solar radiation (SR; R^2 = 0.14) and temperature-humidity index (THI; R^2 = 0.12) were the most important variables in the summer; whereas, maximum temperature (TMAX; R^2 = 0.07) and THI (R^2 = 0.05) were the most important variables over the winter. During equation development, Arias and Mader (2011) found that multicollinearity was present when including THI and daily mean ambient temperature (Ta) in models that also included daily minimum (TMIN) and maximum temperatures (TMAX). Thus, the authors ran regression analyses for summer, winter, and overall (a combination of summer and winter data) models including only THI, Ta, DMI, SR, wind speed (WS), relative humidity (RH), and precipitation (PP) or only TMAX, TMIN, DMI, SR, WS, RH, and PP as possible predictor variables. The 2 overall models explained the largest amount of variation in finishing cattle WI (R^2 = 0.65), and minimum temperature (partial R^2 = 0.56) or THI (partial R^2 = 0.57) explained most of the variation in the respective equation.

In a 4-yr study, Sexson et al. (2012) measured daily WI on finishing steers throughout the summer months (April to October) in Colorado. Water intake was collected using pen (~18 steers/pen) water meters with 2 pens sharing a water fountain. The authors analyzed the impact of 24 linear and quadratic animal and environmental variables and 4 levels of categorical variables on predicting steer WI. The final prediction model (R^2 = 0.32) consisted of 14 linear and quadratic variables, including measures of temperature, humidity, sea level pressure, body weight, and wind speed. Additionally, these authors found that dry matter intake was not an important predictor of WI for finishing steers.

Winchester and Morris (1956) estimated WI based on multiple datasets of dairy and beef cattle, including *Bos indicus* and *Bos taurus* breeds, and accounted for temperature, body weight, and dry matter intake in the calculations. Water intakes reported in those tables included water consumed through feed and free drinking water. The committee on nutrient requirements of beef cattle developed growing and finishing WI equations based on the Winchester and Morris (1956) tables, but replaced temperature with current-effective temperature index (CETI), which is calculated using relative humidity, hours of sunlight, wind speed, and current temperature (NASEM, 2016). The WI equation (R^2 = 0.997) for growing cattle is suggested for animals that weigh between 180 to 400 kg shrunk body weight (SBW), gaining 0.9 kg/d, and exposed to CETI between 4 to 32 °C. The finishing steer WI equation (R^2 = 0.997) is suggested for animals weighing between 270 to 500 kg SBW, gaining 1 kg/d, and experiencing CETI from 4 to 32°C. Since the Winchester and Morris (1956) WI estimates included WI from feed and drinking WI, the NASEM (2016) equations also predicts total WI.

The most recent WI equations were developed using data from a total of 579 growing steers fed under *ad libitum* or slick bunk management and collected over the summer or winter in Oklahoma (Ahlberg et al., 2018). In this study, WI and DMI were measured on an individual animal basis using an Insentec Roughage Intake Control System (Hokofarm Group, The

Netherlands). The authors developed *ad libitum*, slick bunk, winter, summer, and overall (included all data) WI models. All models included DMI, mid-test metabolic body weight (MWTS), average ambient temperature (TAVG), average daily relative humidity (HAVG), average daily wind speed (WSPD), and total daily solar radiation (SRAD), and model R^2 ranged from 0.34 to 0.41. The variables that explained most of the variation in WI were DMI (partial R^2 = 0.124) and TAVG (partial R^2 = 0.194) in the overall model, DMI (partial R^2 = 0.155) and TAVG (partial R^2 = 0.137) in the summer model, DMI (partial R^2 = 0.290) in the winter model, DMI (partial R^2 = 0.150) and TAVG (partial R^2 = 0.190) in the slick bunk model, and MWTS (partial R^2 = 0.110) and TAVG (partial R^2 = 0.230) in the *ad libitum* model.

The current feedlot WI prediction equations include solar radiation, dry matter intake, or both as predictor variables; however, these variables may be more difficult for producers to obtain. Thus, it can be challenging for producers to utilize the published WI equations effectively. As such, more research is needed to examine the predictive ability of WI equations when SR, DMI, or both are excluded from the model.

EVALUATING WATER INTAKE PREDICTION EQUATIONS

To understand the predictive ability, WI equations must be evaluated with an independent dataset for different production scenarios. Currently, there is little research evaluating published WI equations. Zanetti et al. (2019) evaluated the predictive ability of 8 published WI equations (Ahlberg et al., 2018; Sexson et al., 2012; Arias and Mader, 2011; CSIRO, 2007; Meyer et al., 2006; Hicks et al., 1988) to predict WI for Nellore (*Bos indicus*) cattle in Brazil. Thus, the authors found that all equations, which were primarily developed using data from *Bos taurus* cattle, over predicted WI for *Bos indicus* cattle. Ahlberg et al. (2018) briefly evaluated WI equations including their overall WI equation, and the Arias and Mader (2011) and Winchester and Morris (1956) equations. The authors examined how these equations predicted WI for an independent dataset of growing steers fed *ad libitum* over the winter and compared the correlations between observed and predicted WI using individual WI and averaged pen WI. The authors found that correlation coefficients for observed versus predicted WI for their overall WI equation, the Arias and Mader (2011) equation, and the Winchester and Morris (1956) equation were 0.49, 0.51, and 0.49 for individual WI, respectively, and 0.68 and 0.63 for averaged pen WI, respectively. These authors did not evaluate the Winchester and Morris (1956) equation based on averaged pen WI. The authors noted that the higher correlations for pen WI showed that predicting WI based on pen averages removed the individuality of WI observations among cattle. In the end, the evaluated equations explained similar levels of the variation in WI for growing steers. Lastly, Appuhamy et al. (2016) developed WI equations for lactating dairy cows using literature datasets and split the datasets into 1 that included all data and 1 that was comprised of only datasets that reported both average ambient temperature (TAVG) and mineral (Na and K) concentrations in the diet. Then, WI equations with and without DMI as a predictor variable were developed for both datasets resulting in a total of 4 WI equations. The authors evaluated these equations along with 11 previously published equations against a separate dataset for lactating cows. The authors found that the developed models with DMI or with Na, K, and TAVG predicted WI more accurately compared to equations without DMI or Na, K, and TAVG, respectively. The model including DMI, Na, K, and TAVG, among other variables, predicted intakes with highest accuracy out of all 15 equations evaluated. Additionally, 2 of the previously published equations that included DMI as a predictor variable predicted WI with greatest accuracy compared to other previously published equations. Thus, the authors concluded that it is possible to predict WI for lactating cows accurately even when

DMI or Na, K, and TAVG records were not available, but all of these variables were important predictors of WI.

Since there are many environmental, dietary, and physiological factors that influence cattle WI, more extensive evaluations need to be conducted with independent datasets from a variety of production settings. Specifically, in depth evaluations of current WI equations for growing and finishing feedlot cattle have not been explored.

Conclusions from the literature

Numerous environmental and animal variables have been found to significantly influence cattle WI, but variables remaining in WI prediction models are inconsistent for every production setting. Thus, it may be difficult to develop a single equation that would predict cattle WI for all production scenarios. More extensive research is needed to evaluate the accuracy and precision of current WI equations to predict WI for growing and finishing feedlot steers. In addition, most published WI prediction equations have been developed based on pen WI data for growing and finishing steers or individual WI data for growing steers, but equations have not been developed based on individual WI data for finishing steers. The current equations typically include DMI and SR as predictor variables, but these variables are not always readily available to producers. More research is needed to evaluate the impact of removing DMI, SR, or both from finishing cattle WI prediction equations based on individual animal WI.

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Table 1.1 Cattle free water intakes (WI, L/d) in the U.S. with production type, animal description, and WI collection methods

State[1]	Source[2]	Production Type	Animal Description	*n*	Mean WI (L/d)[4]	Standard Deviation (L/d)	WI Collection Method
CA	1	Beef	Steers and heifers	12	54.6	NR	Pen
CO	2	Beef	Finishing steers	NR	37.1	11.6	Pen
FL	3	Beef	Growing steers, heifers, and bulls	146	30	8.6	Individual
IL	4	Dairy	Lactating cows	19	89.2	19.1	NR
IA	5	Beef	Finishing steers	NR	25.1	NR	Pen
NE	6	Beef	Finishing heifers and steers	1278	24.6	7.2	Pen
NH	7	Dairy	Lactating and nonlactating cows	389	53.5	13.4	NR
NM	8	Beef	Grazing lactating and nonlactating cows	67	57.0	8.2	Individual
OK	9	Beef	Finishing steers	167	36.5	9.4	Pen
OK	10	Beef	Growing steers	579	37.9	7.7	Individual

[1]CA = California; CO = Colorado; FL = Florida; IL = Illinois; IA = Iowa; NE = Nebraska; NH = New Hampshire; NM = New Mexico; OK = Oklahoma.

[2]1-Ittner et al. (1951); 2- Sexson et al. (2012); 3- Brew et al. (2011); 4- Murphy et al. (1983); 5- Hoffman and Self (1972); 6- Arias and Mader (2011); 7- Holter and Urban (1992); 8- Rouda et al. (1994); 9- Hicks et al. (1988); 10- Ahlberg et al. (2018).

[3]NR = not reported.

[4]Treatment means for WI within a source were averaged, and mean and variance estimates for WI were calculated by averaging those values.

CHAPTER II

EVALUATING WATER INTAKE PREDICTION EQUATIONS FOR GROWING AND FINISHING FEEDLOT STEERS

ABSTRACT

Predicting water intake (**WI**) is key to optimize water use on farms. Evaluating WI prediction equations is vital to determine the proper equation to predict WI for various types of cattle. The objective of this study was to evaluate precision and accuracy of published equations for predicting WI of growing and finishing feedlot steers. Individual feed and WI were collected for 243 crossbred Angus steers fed a growing (**GRW**) diet and 46 Angus steers fed a finishing (**FIN**) diet. All steers had access to *ad libitum* feed and water. Individual intakes were measured using an Insentec Roughage Intake Control (**RIC**) system during a 70 d period over the summer and winter for GRW and a 51 d period over the winter for FIN. Days with excessive rain, system failures, or animal processing were removed. Weather variables were obtained from the Mesonet weather station nearest the site (3.2 km W of Stillwater, OK). Individual steer WI were calculated for 42 d during each period based on 8 published WI equations, and observed WI were regressed on predicted WI. Coefficient of determination (**R^2**), root mean square error (**RMSE**), slope, and intercept were determined. Residual predicted WI were regressed on mean-centered predicted WI to calculate mean and linear biases. T-tests were performed to determine if intercepts and slopes were significantly different from 0 and 1, respectively. Mean and linear biases for all evaluated equations were significant ($P < 0.0001$). Equations that included DMI, temperature measures, relative humidity, and solar radiation, among other variables, predicted WI for GRW with highest precision ($R^2 = 0.39$ to 0.41) and greatest accuracy (intercept = 1.33 to 3.60; slope = 0.86 to 1.08). For FIN steers, equations that included DMI, temperature measures, and solar radiation, among others, predicted WI with greatest precision ($R^2 = 0.34$ to 0.37) and accuracy (slope = 0.98 to 1.13; intercept = 0.47 to 3.80). To predict WI with highest levels of accuracy and precision, the equation that included DMI, average temperature, solar radiation, average humidity, metabolic body weight, and wind speed could be used for growing steers while equations that included minimum temperature or temperature-humidity index along with DMI and solar radiation could be used for finishing steers. More research is needed to develop better WI prediction equations for various types of cattle under different feeding and management scenarios.

KEYWORDS: evaluation, feedlot cattle, Insentec, prediction, water intake

INTRODUCTION

Water is an essential nutrient for beef cattle health and productivity (NASEM, 2016). As such, it is important for producers to be able to predict water intakes (WI) of cattle as accurately and precisely as possible, especially during droughts where water may be transported to the farm or when building water systems. Various WI prediction equations encompassing a range of environmental and animal variables have been developed for growing and finishing feedlot steers (Ahlberg et al., 2018a; Arias and Mader, 2011; Hicks et al., 1988; NASEM, 2016). Most of these equations were developed based on pen average WI data (Arias and Mader, 2011; Hicks et al., 1988; NASEM, 2016), and few equations were developed using individual animal WI data (Ahlberg et al., 2018a). Evaluating these WI prediction models using secondary datasets is vital to examine the accuracy and precision of the equations, and to determine which equation may better fit certain production scenarios (Tedeschi, 2006).

Water intake is highly variable among animals (Ahlberg et al., 2018a). Advanced technology such as the Insentec Roughage Intake Control (RIC) control system (Hokofarm Group, The Netherlands) allows researchers to measure individual WI for cattle. Using individual animal WI to evaluate prediction equations enables researchers to examine whether the equations are able to capture variation in individual WI which would become prominent in diverse groups of cattle. The objective of this study was to evaluate the precision and accuracy of published WI equations in predicting individual animal WI of growing and finishing feedlot steers.

MATERIALS AND METHODS

All procedures were approved by the Oklahoma State University's Institutional Animal Care and Use Committee (protocol AG13-18).

Animals and Study Designs

Three datasets were used for evaluation calculations. The first two datasets were subsequent datasets from a multi-year experimental protocol used to develop the equations reported by Ahlberg et al. (2018a). Briefly, each group consisted of crossbred Angus steers (Dataset 1 *n* = 124, arrival BW = 237 ± 27 kg; Dataset 2 *n* = 119, arrival BW = 259 ± 29 kg). Steers were purchased by a cattle order buyer from multiple Oklahoma markets (Dataset 1 *n* = 92;

Dataset 2 *n* = 27) or procured from the Oklahoma State University Field Research Service Unit (Stillwater, OK) herds (Dataset 1 *n* = 32; Dataset 2 *n*= 92) and shipped to the Willard Sparks Beef Research Center (WSBRC) in Stillwater, Oklahoma in mid-July 2017 (Dataset 1) or the beginning of January 2018 (Dataset 2). All steers were weighed, given a visual identification tag and an electronic identification (eID) tag, administered an oral (Safeguard; Merck Animal Health, Madison, NJ) and injectable (Dectomax®; Zoetis, Parsippany, NJ) anthelmintic, and administered a metaphylactic antibiotic (Excede®; Zoetis). Steers were vaccinated with a 7-way Clostridial bacterin/toxoid (Vision® 7 with Spur; Merck Animal Health) and a respiratory vaccine (Titanium 5 + PH-M; Elanco, Greenfield, IN).

Approximately two weeks after animals were processed, steers were allocated into 1 heavy and 1 light weight block (2 groups/block) with approximately 30 animals per pen and groups were randomly allocated to 1 of 4 pens. All 4 pens were equipped with an Insentec Roughage Intake Control (**RIC**) system (Hokofarm Group, The Netherlands) where each pen consisted of 6 feed bunks and 1 water bunk. Each bunk allows only one animal to enter at a time. Additional information on the RIC system and settings can be found in Ahlberg et al. (2018a). Briefly, as each animal enters the bunk, the RIC system scans the animal's eID and calculates the difference between the beginning and ending weights for each feeding and drinking event to determine the animal's intake. Each pen had 31 X 11 m of space and provided 9 X 11 m of roof covering the feeding and drinking areas.

Once allocated to pens, steers went through a 21-d acclimation period to adjust to the feed and water intake system. Following this period, the animals underwent a 70-d *ad libitum* feed and water intake period from early September to mid-November 2017 (Dataset 1) and late February to early May 2018 (Dataset 2). On d 0, the steers were weighed and implanted (Compudose®, Elanco). Cattle were weighed every 14 d until the end of the intake period. Cattle were fed a total mixed ration based on cracked corn, Sweet Bran® (Cargill; Dalhart, TX), and grass hay 3 times per d at 0700, 1000, and 1500 h (Table 2.1).

Multiple animals were removed from the study throughout the acclimation and intake periods for health and mechanical issues with the RIC system. During the acclimation periods, five steers were removed from Dataset 1 and one steer was removed from Dataset 2. Additionally, one animal was removed during the intake period for Dataset 1 due to poor overall health issues. An additional steer in Dataset 1 was found to have a systemic infection at the end of the 70-d intake period, that animal's data was excluded from the equation evaluation dataset. During the intake period for Dataset 2, one steer was removed from the study due to issues with utilizing the bunk, and one steer died.

The third dataset consisted of 48 finishing (**FIN**) Angus steers (arrival BW = 431 ± 33 kg). Steers were shipped from Huntsville, MO to WSBRC in Stillwater, OK (796.6 km) in late August 2018. Twenty-four hours after arrival, all steers were vaccinated for common respiratory (Titanium 5+ PH-M; Merck Animal Health) and clostridial (Vision® 7 with spur; Merck Animal Health) diseases, treated for parasites (Noromectin®, Norbrook, Overland Park, KS; Safeguard, Merck Animal Health), implanted (Revalor®-200; Merck Animal Health), and an eID was inserted in the left ear.

After processing, steers were moved into 2 feedlot pens and had *ad libitum* access to a common receiving ration. Seven d following processing, the steers were placed into the WSBRC RIC facility. Animals were granted open access to four Insentec pens which provided them with 24 feed and 4 water bunks for a total area of 1,435.80 m^2, including 412.03 m^2 covered area.

Once placed in the RIC pens, the steers went through a 25-d acclimation period to the feed and water system. Two steers were removed on d 17 of the acclimation period for failure to consistently use the RIC system. Once all steers were fully acclimated to the RIC system, steers were transitioned to a finishing ration over a 24-d concentrate adaptation period using a 5 ration step-up program. Following 7 d on the finishing ration, the steers began the 51 d feed and water intake collection period from late October to mid-December 2018. Steers had access to *ad libitum* feed and were fed once a day at approximately 0900 h. Steers also had *ad libitum* access to water. Steers were weighed on d 0, 1, 33, 50, and 51 of the study.

Water Intake Evaluation Procedures

Ahlberg et al. (2018b) noted that 42 d of concurrent feed and water intake records were sufficient to capture phenotypic intakes across all groups ($r > 0.95$) during a test period. Thus, 42 d were selected from the 70 d or 51 d intake periods for prediction calculations. Days with excessive rain, system failures, missing weather variables, or animal processing were removed. Heavy rain events were excluded to limit the amount of unrecorded water intakes that could occur when animals drink from puddles in the pens. These events were determined using weather observations recorded by researchers to note days with storms or light, moderate, or heavy rains. Three to four d following each heavy rain event or storm were also excluded to allow time for puddles in the pens to evaporate to reduce the likelihood of cattle consuming water from the puddles which would lead to inaccurate WI measurements with the RIC unit. Additionally, days with missing weather variables that are required for input in the water intake equations were excluded.

For datasets 1 and 2, the middle 42 eligible d were selected for evaluation. These nonconsecutive periods spanned from September to November 2017 and from March to May 2018 for datasets 1 and 2, respectively. For FIN, the first 42 eligible d were used, including the seventh d steers were on the finishing ration (d -1) and one weigh day (d 33), during which cattle were out of the RIC pens for less than one hour. The evaluation period for FIN was from October to December 2018.

Once the 42 d were selected, individual event data when ID was 0 or when intakes were 0, and any visit less than 5 seconds in length were removed. Individual daily steer feed or water intakes outside ± 3 SD from the group's average daily intakes or from the individual steer's average daily intakes were removed, which resulted in an average of 2.13%, 1.94%, and 1.81% of intakes removed for datasets 1, 2, and 3, respectively.

For each 42 d period, all weather variables were collected from a nearby Oklahoma Mesonet station, which is located 3.2 km west of Stillwater, OK. Variables obtained were maximum (TMAX), minimum (TMIN), and average (TAVG) ambient temperatures, average relative humidity (HAVG), average wind speed (WS), daily rainfall (RAIN), and total (TSR) and 15 min solar radiation values. The Mesonet station sends data containing three, 5-min averages of the listed weather variables to the Oklahoma Law Enforcement Telecommunications system every 15 min (Brock et al., 1995). This data was totaled or averaged at the end of the day to obtain the appropriate measurement. At the Stillwater Mesonet station, a Vaisala HMP35C probe (Campbell Scientific) was used to measure RH and a thermistor was attached to measure air temperatures at 1.5 m above the ground. Wind speed was measured at 2 m above the ground using a R.M. Young 5103 sensor. A rain gauge, located at 0.6 m above the ground, with a bucket tip measures the amount of rainfall in 0.25 mm increments every 5 min. Solar radiation values were collected using a silicon photodiode-type pyranometer (Licor model 200) that is located adjacent to the station at a height of 1.75 m.

Current Water Intake Equations

The WI prediction equations evaluated included an equation developed by Hicks et al. (1988), 2 developed by Arias and Mader (2011), 2 equations reported in NASEM (2016), and 3 equations developed by Ahlberg et al. (2018a). Those 8 equations are as follows:

Eq. 1 WI (L/d) = -6.0716 + 0.70866*MT + 2.432*DMI – 3.87*PP – 4.437*DS

Equation 1 (model R^2 = 0.74) is an adaptation of the equation developed by Hicks et al. (1988). This equation was developed using average pen WI data collected from 47 crossbred yearling steers. In that experiment, 2 pens containing 7 to 8 steers shared a water tank that measured WI using meters. For this equation, WI is water intake (L/d), MT is maximum temperature (°C), DMI is dry matter intake (kg/d), PP is precipitation (cm), and DS is dietary salt (%). A dietary salt level of 0.25% was used in equation 1 calculations for all datasets. Total daily rainfall (cm) was used as the input for precipitation; however, these values were low since days with heavy rain were excluded from the datasets.

Eq. 2a WI (L/d) = 5.92 + 1.03*DMI + 0.04*SR + 0.45*TMIN

Eq. 2b WI (L/d) = -7.31 + 1.00*DMI + 0.04*SR + 0.30*THI

Equations 2a (model R^2 = 0.65) and 2b (model R^2 = 0.65) were developed by Arias and Mader (2011) using pen WI data collected from 1,278 steers and heifers. The authors measured WI using water meters shared by a group of animals and calculated individual animal WI based on that data. Total daily solar radiation (W/m^2) is SR, TMIN is daily minimum ambient temperature (°C), and THI is temperature-humidity index. Temperature-humidity index was calculated using the equation THI = 0.8 Ta + [(RH/100) (Ta -14.4)] + 46.4 where Ta is mean ambient temperature (°C) and RH is relative humidity (%).

Eq. 3 WI (L/d) = $7.3 + 0.0805*SBW - 0.00008*SBW^2 - 1.225*CETI + 0.0411*CETI^2 + 0.0023268*SBW*CETI$

Eq. 4 WI (L/d) = $6.336 + 0.1057*SBW - 0.0000963*SBW^2 - 1.6*CETI + 0.056*CETI^2 + 0.00226*SBW*CETI$

Equations 3 (model $R^2 = 0.997$) and equation 4 (model $R^2 = 0.997$) were reported in NASEM (2016) and were developed using total WI data measured using water meters for pens of various classes of animals reported in Winchester and Morris (1956), which includes WI from feed. Equation 3 was suggested for use in predicting WI for growing steers, heifers, and bulls while equation 4 was suggested for use in predicting WI for finishing steers. Shrunk body weight (kg) is SBW, and CETI is current effective temperature index (°C). Current effective temperature index was calculated using the following equation:

$$CETI = 27.88 - (0.456*Tc) + (0.010754*Tc^2) - (0.4905*RHc) + (0.00088*RHc^2) + (1.1507*(WS/3.6)) - (0.126447*(WS/3.6)^2) + (0.019867*Tc*RHc) - (0.046313*Tc*(WS/3.6)) + (0.41267*HRS)$$

where Tc is current temperature (°C), RHc is current relative humidity (%), WS is wind speed (km/h), and HRS is hours of sunlight. Equations 3 and 4 are the only equations that account for WI from feed. Fifteen-minute SR values greater than 10 W/m^2 were used to determine the total daily hours of sunlight (HRS) needed for the CETI calculations (Eq. 3 and 4).

Eq. 5 WI (L/d) = -4.18 + 2.00*DMI + 0.22*MWTS + 0.57*TAVG - 0.15*HAVG – 0.16*WSPD + 0.14*SRAD

Eq. 6 WI (L/d) = -4.24 + 1.76*DMI + 0.22*MWTS + 0.26*TAVG – 0.09*HAVG - 0.06*WSPD + 0.13*SRAD

Eq. 7 WI (L/d) = 0.71 + 2.63*DMI – 0.009*MWTS + 0.76*TAVG – 0.06*HAVG – 0.11*WSPD + 0.23*SRAD

Equations 5 (model R^2 = 0.40), 6 (model R^2 = 0.39), and 7 (model R^2 = 0.41) were developed by Ahlberg et al. (2018a) using WI data collected from 579 steers on an individual animal basis. Equation 5 was developed using data from growing steers fed under *ad libitum* and slick bunk management during the summer and winter. Equation 6 was developed for growing steers fed under both management strategies during only the winter. Equation 7 was developed for growing steers fed during both seasons under only *ad libitum* feeding management. In these equations, WI is daily water intake (L/d), DMI is dry matter intake (kg/d), MWTS is mid-metabolic body weights (kg), TAVG is average daily temperature (°C), HAVG is average daily relative humidity (%), WSPD is average daily wind speed (km/h), and SRAD is average daily solar radiation (MJ/m^2). Metabolic body weights on d 21 of each evaluation period were used for MWTS. Equations 5 to 7 calculate free WI and do not include WI from feed.

Observed DMI collected during the intake periods in this study were used in Equations 1, 2a, 2b, 5, 6, and 7 to limit the added error that could occur by predicting DMI with published DMI equations.

Statistical Analysis

Datasets 1 and 2 were combined (**GRW**) during analysis because the steers had similar intakes, BW, and were fed the same diet composition. Summary statistics were calculated using the MEANS procedure of SAS 9.4 (SAS Inst. Inc., Cary, NC). Observed free drinking WI were regressed on predicted WI for each of the 8 published WI equations. Coefficient of determination (**R^2**), root mean square error (**RMSE**), slope, and intercept were obtained using the REG procedure in SAS 9.4. Based on Tedeschi (2006), R^2 was used to evaluate equation precision where high R^2 characterized high precision, and slope and intercept were used to evaluate equation accuracy where a slope close to 1 and intercept close to 0 defined high accuracy. Root mean square error was also used to evaluate model precision where low RMSE characterized greater precision. Differences in means for weather variables between GRW and FIN were determined with the MIXED procedure in SAS using the LSMEANS statement.

Linear and mean biases were calculated based on St-Pierre (2003). The authors explained that centering the predicted WI to the average daily predicted WI shifts the intercept to be estimated at the average WI instead of 0. Thus, each animal's daily predicted WI were centered (centeredWI; predicted daily WI – average predicted WI) to the average daily predicted WI for the herd for each equation. Residual WI (residualWI; observed WI – predicted WI) for each equation (n = Eq1 . . . Eq7) were regressed on centeredWI for each equation (n = Eq1 . . . Eq7). The final regression model was:

$$\text{residualWI}_n = \beta_0 + \beta_1 \text{ centeredWI}_n$$

Mean bias was the intercept value from the mean-centered regression and the *P*-value was determined based on a t-test where H_0: $\beta_0 = 0$ and H_1: $\beta_0 \neq 0$. Positive and negative mean biases indicate that the equations under and over predicted observed WI, respectively. Linear bias was the slope of the mean-centered regression and the *P*-value was determined by performing a t-test where H_0: $\beta_1 = 1$ and H_1: $\beta_1 \neq 1$. Positive and negative linear biases indicate that slope was greater than 1 or less than 1, respectively.

RESULTS AND DISCUSSION

Animal and Environmental Variables

Water intakes tend to be greater in the summer than the winter (Sexson et al., 2012; Ahlberg et al., 2018a) as cattle attempt to cope with heat stress related to higher temperatures and humidity (Morrison, 1983). Growing steer WI were 23% greater and 2.12 L/d more variable than FIN steers (Table 2.2). A small difference was observed between minimum WI between groups; however, GRW steers had maximum WI that were 33 L/d greater. All mean weather variables were greater ($P < 0.01$) in the GRW dataset except HAVG and rain (Table 2.3). Relative humidity was greater ($P < 0.01$) in the FIN dataset. Selection criteria for the 42 d evaluation periods involved removing days with excessive rainfall, which explains why rain was not different ($P = 0.44$) between the datasets. Dry matter intakes were not different between datasets (GRW = 11.05 kg/d; FIN = 12.33 kg/d).

Growing Steers: Equation Evaluation

Intercepts, slopes, and mean and linear biases were used to evaluate the accuracy of published equations. Mean and linear biases were significant ($P < 0.01$) for all equations (Table 2.4). Equations 1, 3, 4, 5, and 7 over predicted observed WI as denoted by negative mean biases, while equations 2a, 2b, and 6 under predicted observed WI as indicated by positive mean biases. On average, equations 1, 5, and 6 predicted WI for GRW steers closest to observed values (mean bias = - 0.72, - 1.33, and 1.19 L/d, respectively). Intercepts were closest to 0 for equations 6 (1.33), 2a (3.60), and 5 (3.60), and slopes were closest to 1 for equations 6 (1.00), 2b (1.00), and 2a (1.08). Although the slopes were not substantively different from 1 in those equations, linear biases were still statistically significant because the mean-centered observed versus predicted WI regressions had nearly 10,000 datapoints for each equation. However, these equations were still useful for predicting WI even though the biases were statistically significant. In Figure 2.1, equations 1, 2a, 2b, 5, and 6 have regression lines that are most uniform with the equality lines which corresponds to the small mean and linear biases reported for these equations. These results indicate that equations 2a, 5, and 6 predicted WI for growing steers with greatest accuracy. Equations 5 and 6 were developed with a combined summer and winter dataset or only winter data, respectively, and using individual WI for growing steers (Ahlberg et al., 2018a). Since the dataset used in this study utilized growing steer WI data collected over the summer and winter, it was expected that equations 5 and 6 would perform well for the evaluated dataset. However, it was interesting that equation 2a performed better than 2b though both equations were developed with finishing steer and heifer pen WI data collected over the summer and winter (Arias and Mader, 2011). The only difference between the two is that equation 2a included TMIN as one of the predictor variables; whereas, equation 2b included THI.

Equation 4 predicted WI furthest from observed WI (mean bias = -7.75), had the largest linear bias (-0.58), and intercept furthest from 0 (16.96) indicating that it was the least accurate equation to predict WI for growing steers. Similarly, equation 3 had a large intercept (16.04) and linear bias (-0.51) showing that it predicted WI with low accuracy as well. Since equation 4 was developed to predict WI for finishing steers, it was not surprising that it was the least accurate for growing steers and overpredicted WI by the greatest margin. In addition, the average starting and ending shrunk body weights (SBW) for GRW was calculated to equal 327 and 413 kg based on Table 2.2. The minimum and maximum CETI for the GRW dataset was 7.60 and 35.12°C (not reported). The CETI and SBW ranges for GRW were relatively close to the ranges suggested when using equation 3 for growing steer predictions (180 to 400 kg SBW; 4 to 32°C; NASEM, 2016) which should not greatly influence the predictions. Thus, equation 3 was likely inaccurate at predicting WI for growing steers because it only included SBW and CETI as major predictor variables. Individual input variables for calculating CETI may not be most properly influencing the variable. Current effective temperature index was calculated using WS, HAVG, TAVG, and hours of sunlight. Since those variables were included in the CETI calculations, WS, HAVG, TAVG, and hours of sunlight had a smaller overall impact on predicting WI. It is possible that WI could be more accurately predicted using other variables that were not included in equations 3 and 4 such as DMI and SR, which were included in equations 2a, 5, and 6 that most accurately predicted intakes. This corresponds with various studies which found that DMI (Hicks et al., 1988; Meyer et al., 2006; Cardot et al., 2008; Ahlberg et al., 2018a; Zanetti et al., 2019) and SR (Arias and Mader, 2011; Ahlberg et al., 2018a) were important variables influencing cattle WI.

In addition, equations 3 and 4 were developed using tabular values of total WI, including WI from feed, (Winchester and Morris, 1956) instead of using only drinking WI data as obtained in this study, which may have contributed to the decreased predictive ability of those equations. For instance, the average WI consumed from feed in the GRW dataset was back calculated based on average DMI (11.1 kg/d; Table 2.2) and the dry matter percent of the diet (70.1 %; Table 2.1) and was equal to 4.7 L/d. Total WI for GRW, or drinking WI plus WI from feed, was 39.2 L/d. Thus, equation 3 under predicted total WI by only 1.8 L/d and equation 4 over predicted total WI by 3.1 L/d which means equations 3 and 4 were the 4th and 5th most accurate equations when including WI consumed from feed.

It is important to evaluate precision of the WI equations from varied conditions to examine how well the equations predict WI values that are close together. All equations resulted in similar RMSE values ranging from 6.79 to 7.55 (Table 2.4). Therefore, R^2 and the range of predicted intakes based on Figure 2.1 were used to evaluate equation precision. Equations 1, 5, and 7 accounted for the greatest variation in WI (R^2 = 0.39, 0.41, and 0.41). Additionally, it is essential that WI equations predict a wide range of intakes since WI has been found to be variable among individual animals (SD = 4.84 to 13.07 L/d; Ahlberg et al., 2018a). Equations 1, 5, and 7 predicted WI with ranges of ~51, 53, and 58 L/d (Figure 2.1) which were higher than other equations. Equation 4 also predicted a large range of WI (~56 L/d); however, it resulted in one of the smallest R^2 (0.27), along with equation 3 (R^2 = 0.27). Equations 3 and 4 also resulted in the largest spread of datapoints around the regression lines (Figure 2.1). Therefore, these results indicate that equations 1, 5, and 7 predicted WI with greatest precision, while equations 3 and 4 were the most imprecise. These results emphasize the importance of including DMI and measures of temperature, such as TMAX or TAVG, in WI prediction equations as equations that included these variables predicted WI with highest precision (Eq. 1, 5, and 7) while those that did not include these as major variables independently predicted intakes with poor precision (Eq. 3 and 4). Numerous studies have found that measures of temperature positively influence WI (Murphy et al., 1983; Meyer et al., 2006; Sexson et al., 2012; Zanetti et al., 2019). Additionally, equations 5 and 7 were developed using individual WI for growing steers collected with the WSBRC Insentec RIC unit (Ahlberg et al., 2018a) similar to how WI were obtained in this study which could explain the high levels of precision.

Ahlberg et al. (2018a) also evaluated equation precision using an individual dataset from growing steers fed *ad libitum* over the winter by comparing results from individual observed versus predicted WI regressions based on their overall model, the Arias and Mader (2011) model, and the Winchester and Morris (1956) model. The authors found that the 3 models resulted in R^2 of 0.49, 0.51, and 0.49, respectively, which were higher than all R^2 reported for growing steers in this study. Although it was not directly mentioned in the study, the validation dataset in Ahlberg et al. (2018a) likely included 100 to 120 steers, similar to the number of animals in the other datasets described in that study. The current study included individual WI records from 243 steers. It may be more difficult to precisely predict WI on an individual basis for a larger group of cattle due to the variability among animals which could explain the lower R^2 obtained in this study. When reported means and standard deviations were averaged across groups, the equation development datasets reported in Ahlberg et al. (2018a) consisted of similar animal intakes, body weights, and environmental conditions to the GRW dataset with the exception of the lower SD for HAVG in the Ahlberg et al. (2018a) dataset (4.53%) compared to this study (11.77%). Thus, differences in animal measurements and weather variables were likely not influential in resulting in the lower R^2 values obtained during equation evaluation in this study.

Tedeschi (2006) suggests that precision may be more important than accuracy when evaluating prediction equations as prediction models that are accurate and imprecise are impractical. Thus, the best WI equations for growing steers were determined by selecting equations in the following order: equations that were both precise and accurate, equations that were most precise, and equations that were most accurate. Equation 5 was the best overall WI prediction equation for growing steers as it predicted WI precisely and accurately. In the following order, the next best prediction equations were equations 7, 1, 6, and 2a. It is important to note that equations 1 and 2a were developed for finishing steers that experienced different weather conditions but were still able to adequately predict WI for the GRW dataset.

Finishing Steers: Equation Evaluation

Mean and linear biases were significant ($P < 0.01$) for all equations when predicting WI for finishing steers (Table 2.4). All equations, except 2a and 2b, over predicted WI as shown by negative mean biases. Equations 2a and 2b predicted intakes closest to observed values (mean bias = 3.42 and 3.44, respectively). These equations resulted in slopes closest to 1 (1.13 and 0.98, respectively), and thus had smallest linear biases (0.128 and -0.015; respectively). As with the GRW dataset, these small linear biases were still significant likely due to the large dataset (~2,000 datapoints). Intercepts were closest to 0 for equations 2a (0.47) and 6 (-1.00). These results indicate that equations 2a and 2b were the most accurate WI equations for finishing steers which can also be examined in Figure 2.2 where the regression lines were most parallel to the equality lines. These equations performed with highest accuracy and were developed using WI data from heifers and steers finished in the summer and winter (Arias and Mader, 2011) similar to the FIN evaluation dataset.

Equations 4 (slope = 0.51; intercept = 6.68), 3 (slope = 0.45; intercept = 11.48), 1 (slope = 0.52; intercept = 9.88), and 7 (slope = 0.53; intercept = 8.77) had intercepts furthest from 0 and slopes furthest from 1 which indicates that these equations predicted WI with similar levels of inaccuracies. These inaccuracies can be visualized in Figure 2.2 as the regression lines for these equations deviate furthest from the equality lines. Additionally, equations 4, 5, and 6 predicted WI furthest from observed values (mean bias = -12.74, -11.70, and -11.83, respectively). Thus, all equations predicted WI inaccurately for finishing steers except equations 2a and 2b. However, equations 3 and 4 predict total WI which includes drinking WI and WI from feed; whereas, this study only predicted drinking WI. On average, WI from feed was calculated from DMI (12.3 kg/d; Table 2.2) and the dry matter percent of the finishing diet (75.6%; Table 2.1) and was equal to ~4 L/d. When adding WI from feed to the observed WI (26.6 L/d; Table 2.2), total WI was equal to 30.6 L/d. Thus, equations 3 and 4 predicted WI more accurately, or over predicted WI by only 2.7 and 8.7 L/d, respectively, when WI from feed was included.

Since the Ahlberg et al. (2018a) equations (Eq. 5-7) and equation 3 (NASEM, 2016) were developed for growing steers, it was expected that these equations would perform poorly for the FIN dataset. It was more surprising that equations 1 and 4 did not predict WI more accurately for finishing steers. This was likely because the equations did not include SR as a predictor variable and equation 4 did not include DMI. As mentioned earlier, SR and DMI tend to be important variables for WI predictions (Hicks et al., 1988; Meyer et al., 2006; Cardot et al., 2008; Arias and Mader, 2011; Ahlberg et al., 2018a). In addition, the average starting and ending SBW for the FIN dataset (~510 and 592 kg, respectively) was above the 270 to 500 kg SBW range suggested for equation 4 (NASEM, 2016) and the 180 to 400 kg SBW range suggested for equation 3 (NASEM, 2016) which could contribute to errors from those equations.

Similar to the GRW results, the RMSE values from the observed versus predicted WI regressions in the FIN dataset were similar for all equations and ranged from 5.35 to 6.24. So, the most precise equations were determined to be those with high R^2 values and the ability to predict an observed range of WI. Equations 5, 2b, 2a, and 7 accounted for the greatest variation in intakes (R^2 = 0.37, 0.36, 0.34, and 0.34, respectively; Table 2.4), and equations 1 and 7 predicted WI with greatest ranges (~52 L/d each; Figure 2.2). These results suggest that equations 2a, 2b, 5, and 7 were the most precise equations to predict WI for finishing steers. As discussed previously, equations 5 and 7 were developed using individual WI collected on growing steers fed a growing diet (DM = 70.04 to 74.02%; Ahlberg et al., 2018a) using the WSBRC RIC unit. So, although those equations were based on growing steer WI, the use of the RIC unit to collect individual WI could explain why these equations predicted WI precisely for finishing steers.

The graphs for equations 3 and 4 appear truncated in that the equations seem to only predict WI between ~25-50 and 30-55 L/d, respectively (Figure 2.2). The shape of the graphs emphasize that these equations predicted relatively small ranges in WI (~25 L/d each) compared to equations 1, 5, 6, and 7. This aligns with the low percent of variation in WI (R^2 = 0.14 each) that these equations explained. These equations resulted in the largest RMSE values (Eq. 3 = 6.23; Eq. 4 = 6.24) as well. Equations 2a and 2b also predicted small ranges of WI (~22 and 27 L/d, respectively), but resulted in relatively large R^2. Thus, equations 3 and 4 were the most imprecise equations to predict WI for finishing. This may have been because the equations were developed based on tabular WI values reported in Winchester and Morris (1956). Using tabular values could have removed a large proportion of the variation in WI that would have been accounted for if a larger dataset of daily individual animal WI were obtained, which would explain the decreased predictive ability of the equations.

As with the GRW equations, the best equations for finishing steers were determined by selecting equations that performed with greatest precision and accuracy, greatest precision, and then greatest accuracy. Equations 2a and 2b were the best equations to predict pen average WI for finishing steers with high levels of precision and accuracy, but these equations did not represent the range in WI observed with individual animals. The next best equations were 5 and 7 since these performed with high levels of precision. However, the WI equations should be evaluated for steers consuming a finishing diet over the summer since WI is typically higher and heat stress becomes a major concern for producers.

Although several equations performed well for GRW and FIN datasets, the equations evaluated in this study explained a maximum of 41% of WI for individual growing steers (Eq. 5 and 7) and 37% of WI for finishing steers (Eq. 5). These small R^2 suggest that the even the best equations could not explain 59% or 63% of the variation in growing and finishing steer WI, respectively, which suggests that it may be possible to develop better prediction equations. More research is needed to develop equations that can accurately predict greater ranges in WI for feedlot cattle.

Producers can utilize published equations to assist in water resource management and development. For example, a producer can predict WI for the herd in order to determine the amount of water needed during development of water delivery systems. Lastly, an appropriate equation must be selected based on its predictive ability and the animal and environmental input variables accessible to the producer. It is possible to adequately predict WI using published equations, but predictions may be limited by the input variables that are available to producers. For instance, if a producer does not have access to solar radiation data, then they must select an equation that does not require solar radiation as an input variable. Thus, producers would be required to select a less accurate and precise model to fit their production setting.

CONCLUSION

Current WI prediction equations were able to predict WI for growing and finishing steers with moderate levels of precision and accuracy. The best WI equations for growing steers were equation 5 (combined; Ahlberg et al., 2018a) followed by equations 7 (*ad libitum*; Ahlberg et al., 2018a) and 1 (Hicks et al., 1988). The best WI equations for finishing steers were equations 2a and 2b (Arias and Mader, 2011) followed by equation 5 (combined; Ahlberg et al., 2018a). Additionally, dry matter intake and solar radiation seem to be important WI predictor variables for feedlot cattle as these variables were usually included in equations that performed with greatest precision and accuracy. However, the evaluated equations could not predict a large amount of the variation in individual WI for both growing and finishing steers. More research is needed to develop better WI prediction models for feedlot cattle fed throughout a variety of environmental conditions.

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Table 2.1. Composition of growing and finishing diets during the 70 d intake period for growing steers and the 51 d intake period for finishing steers

Item	Growing	Finishing
Ingredients, % DM		
Sweet Bran[1]	54.8	20.0
Prairie hay	30.0	8.0
Dry rolled corn	10.0	62.0
Dry supplement[2,3]	5.2	5.0
Liquid supplement[4]	-	5.0
Nutrient Analysis, DM basis[5]		
DM, %	70.1	75.6
CP, %	16.2	13.6
ADF, %	22.8	10.9
TDN, %	70.1	87.1
NEm, Mcal/kg	1.64	2.16
NEg, Mcal/kg	1.04	1.48
Ca, %	0.62	0.51
P, %	0.63	0.52
Mg, %	0.31	0.23
K, %	1.06	0.92

[1]Wet corn gluten feed (Cargill, Dalhart, TX).
[2]Dry supplement in growing diet was composed of 41% ground corn, 21.7% wheat midds, 27.9% limestone, 0.95% magnesium oxide, 0.35% salt, 6.45% urea, 0.11% copper sulfate, 0.11% manganese oxide, 0.05% selenium, 0.57% zinc sulfate, 0.29% Vitamin A, 0.08% Vitamin E, 0.18% Tylan-40, and 0.29% Rumensin-90.
[3]Dry supplement for finishing diet was composed of 42.6% ground corn, 27.1% calcium carbonate, 20.6% wheat midds, 0.49% magnesium oxide, 0.92% salt, 6.5% urea, 0.12% copper sulfate, 0.15% manganese oxide, 0.08% selenium, 0.47% zinc sulfate, 0.29% Vitamin A, 0.09% Vitamin E, 0.008% Vitamin D, 0.30% Rumensin-90, and 0.19% Tylan-40.
[4]Liquid supplement in both diets was primarily composed of 45.9% corn steep, 36.2% cane molasses, 6% hydrolyzed vegetable oil, 5.2% water, 1.2% urea, and 0.1% xanthan gum.
[5]Nutrient analyses were conducted by wet chemistry at a commercial laboratory (Servi-Tech Laboratories, Dodge City, KS).

Table 2.2. Summary statistics for growing (GRW)[1] and finishing (FIN)[1] steers during the 42 d evaluation period

Variable[2]	Dataset	Mean	SD	Minimum	Maximum
WI, L/d	GRW	34.5	8.8	7.7	86.6
	FIN	26.6	6.7	6.8	53.7
DMI, kg/d	GRW	11.1	2.1	3.6	19.1
	FIN	12.3	2.6	3.5	20.8
Starting weight[3], kg	GRW	340.8	36.2	250.5	421.2
	FIN	531.1	47.0	393.5	612.7
Ending weight[4], kg	GRW	431.1	45.5	283.9	549.4
	FIN	616.4	49.5	504.7	714.2

[1]The total number of steers in the 42 d evaluation datasets were 243 for GRW and 46 for FIN. Intakes outside 3 SD of individual animal's daily intakes or the herd's daily intakes were removed.
[2]WI = daily water intake; DMI = daily dry matter intake.
[3]Starting weight is the body weight of all steers on the first day of evaluation.
[4]Ending weight is the body weight of all steers on the last day of evaluation.

Table 2.3. Summary of average daily weather variables used in equations throughout the 42 d evaluation period

Variable[1]	Dataset[2]	Mean	SD	Range
TAVG, °C	GRW	15.12[a]	7.17	28.21
	FIN	6.33[b]	5.86	22.67
TMIN, °C	GRW	7.83[a]	7.88	30.32
	FIN	0.24[b]	5.67	21.03
TMAX, °C	GRW	22.28[a]	7.44	29.59
	FIN	13.28[b]	7.31	27.77
HAVG, %	GRW	62.94[b]	11.77	58.63
	FIN	69.31[a]	9.66	47.98
WS, km/h	GRW	12.81[a]	4.99	22.11
	FIN	10.30[b]	4.78	21.73
TSR, MJ/m^2	GRW	16.78[a]	6.43	26.10
	FIN	9.63[b]	4.70	14.34
Rain, cm	GRW	0.07	0.30	1.85
	FIN	0.03	0.09	0.48
THI, °C[3]	GRW	59.03[a]	10.28	39.51
	FIN	45.71[b]	9.15	35.84
CETI, °C[4]	GRW	20.28[a]	7.15	27.52
	FIN	9.71[b]	7.00	25.62

[1]TAVG = average daily ambient temperature; TMIN = minimum daily temperature; TMAX = maximum daily temperature; HAVG = average daily relative humidity; WS = average daily wind speed; TSR = total solar radiation; Rain = total daily rainfall; THI= temperature-humidity index; CETI= current effective temperature index.
[2]Averages for GRW are based on combined 42 d weather variables from each dataset of growing steers.
[a,b]Means with different superscripts within variable are different ($P < 0.01$).
[3]THI was calculated based on Arias and Mader (2011).
[4]CETI was calculated based on NASEM (2016).

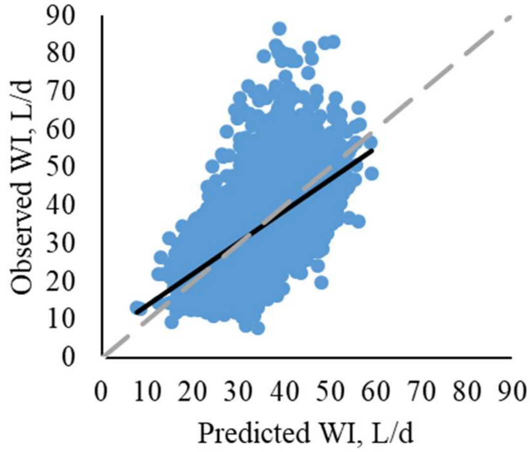
Table 2.4. Results for observed regressed on predicted water intakes (WI) for growing (GRW) and finishing (FIN) steers

		Equation[1]							
Dataset	**Parameters[2,3]**	**1**	**2a**	**2b**	**3**	**4**	**5**	**6**	**7**
GRW	**Pred WI, L/d**	35.2	28.6	29.2	37.4	42.3	35.9	33.3	39.2
	R^2	0.39	0.34	0.31	0.27	0.27	0.41	0.34	0.41
	Slope	0.83	1.08	1.00	0.49	0.42	0.86	1.00	0.75
	Intercept	5.39	3.60	5.40	16.04	16.96	3.60	1.33	4.99
	RMSE	6.91	7.20	7.33	7.53	7.55	6.81	7.19	6.79
	Mean bias[4,5]	-0.72	5.93	5.31	-2.86	-7.75	-1.33	1.19	-4.68
	Linear bias[4,5]	-0.17	0.08	-0.003	-0.51	-0.58	-0.14	-0.004	-0.25
FIN	**Pred WI, L/d**	32.0	23.2	23.1	33.3	39.3	38.3	38.4	33.8
	R^2	0.32	0.34	0.36	0.14	0.14	0.37	0.31	0.34
	Slope	0.52	1.13	0.98	0.45	0.51	0.64	0.72	0.53
	Intercept	9.88	0.47	3.80	11.48	6.68	2.27	-1.00	8.77
	RMSE	5.54	5.46	5.37	6.23	6.24	5.35	5.60	5.47
	Mean bias[4,5]	-5.44	3.42	3.44	-6.67	-12.74	-11.70	-11.83	-7.21
	Linear bias[4,5]	-0.478	0.128	-0.015	-0.546	-0.494	-0.365	-0.282	-0.473

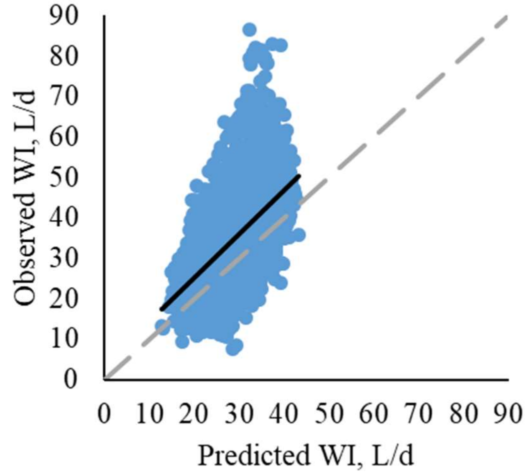
[1]Equation 1 = Hicks et al. (1988); Equations 2a (minimum temperature) and 2b (temperature-humidity index) = Arias and Mader (2011); Equations 3 (growing) and 4 (finishing) = NASEM (2016); Equations 5 (combined), 6 (winter), and 7 (*ad libitum*) = Ahlberg et al. (2018).
[2]Pred WI = average predicted WI; R^2 = coefficient of determination; RMSE = root mean square error.

[3]R^2, RMSE, intercept, and slope were obtained from regressing observed free WI on predicted WI for each equation using PROC REG (SAS 9.4). Pred WI were obtained using PROC MEANS (SAS 9.4).
[4]Mean and linear biases were calculated by regressing residual predicted WI on mean-centered predicted WI for each equation based on St-Pierre (2003). Mean and linear biases were the intercept and slope terms obtained from these regressions, respectively. *P*-values for mean and linear biases were obtained by performing t-tests to determine if intercept = 0 or slope = 1, respectively.
[5]Mean biases were significantly different than 0 and linear biases were significantly different than 1 ($P < 0.01$).

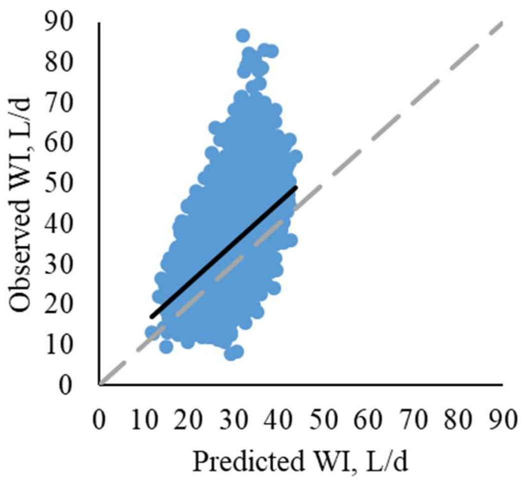
Equation 1



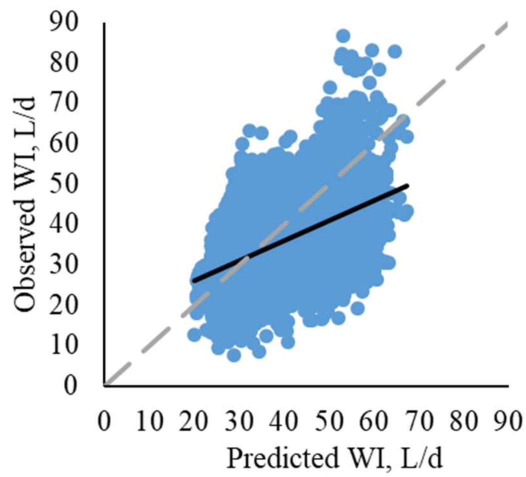
Equation 2a



Equation 2b



Equation 3



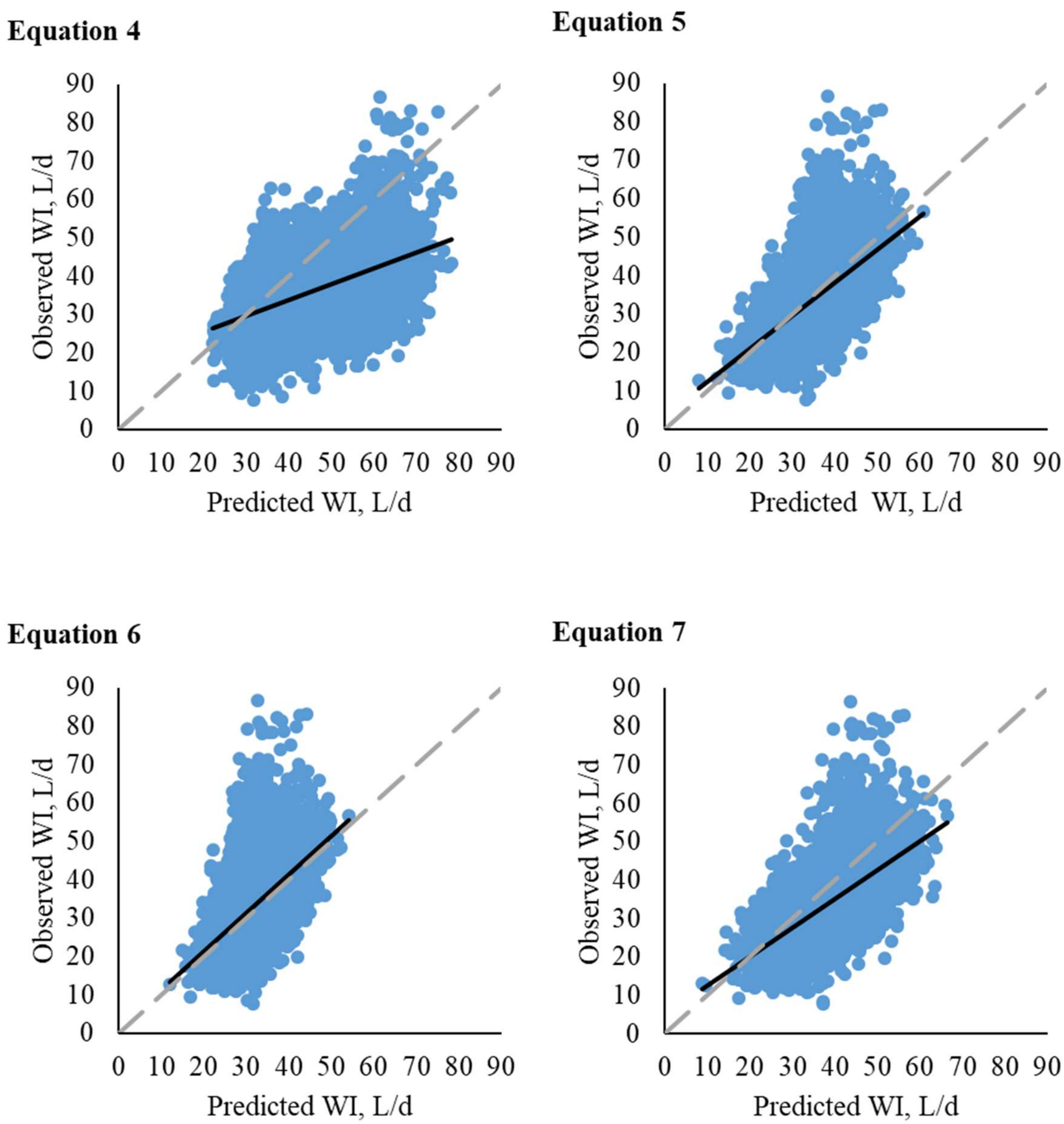
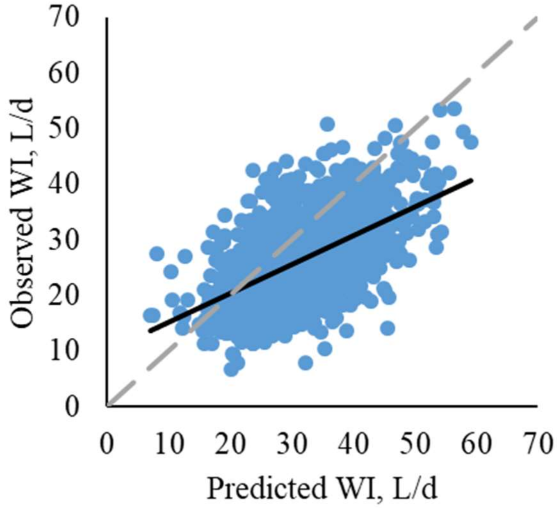
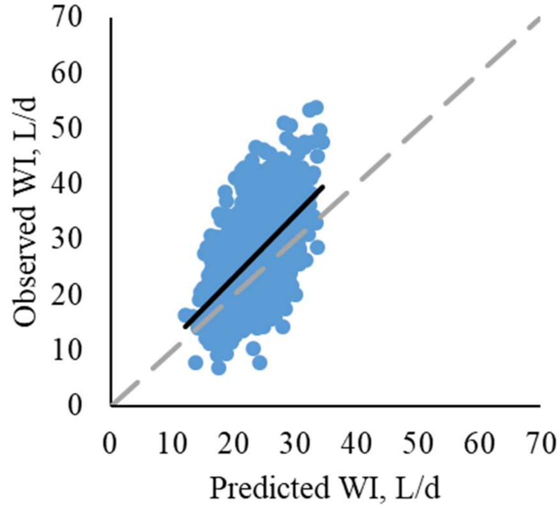


Figure 2.1. Observed vs. predicted individual water intake (WI) plots for growing (GRW) crossbred Angus steers during a 42-d evaluation period. Each panel represents the evaluated equations: Equation 1 = Hicks et al. (1988); Equations 2a (minimum temperature) and 2b (temperature-humidity index) = Arias and Mader (2011); Equations 3 (growing) and 4 (finishing) = NASEM (2016); Equation 5 (combined), 6 (winter), and 7 (*ad libitum*) = Ahlberg et al. (2018). The solid line represents the fit of the regression, and the dashed line represents the equality line.

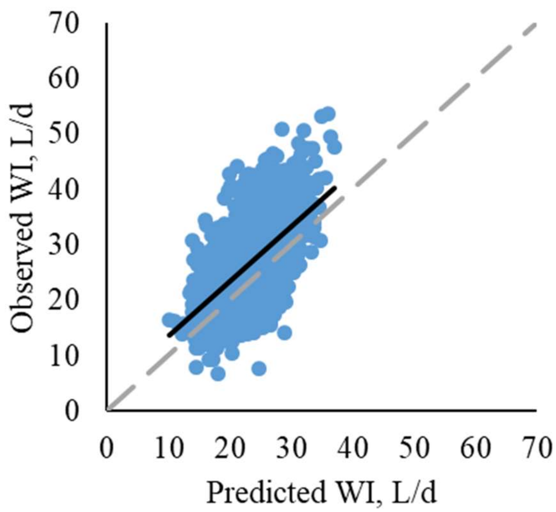
Equation 1



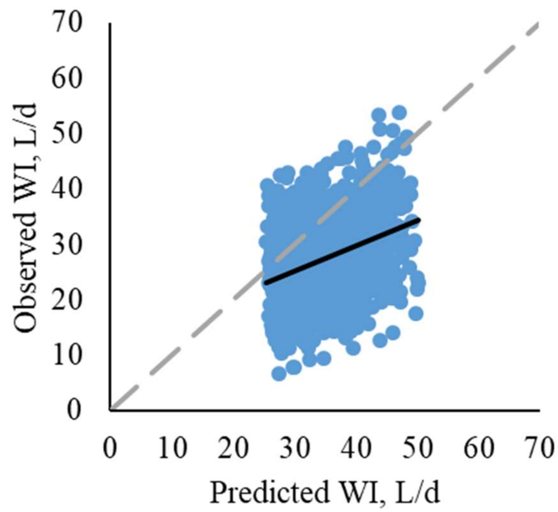
Equation 2a



Equation 2b



Equation 3



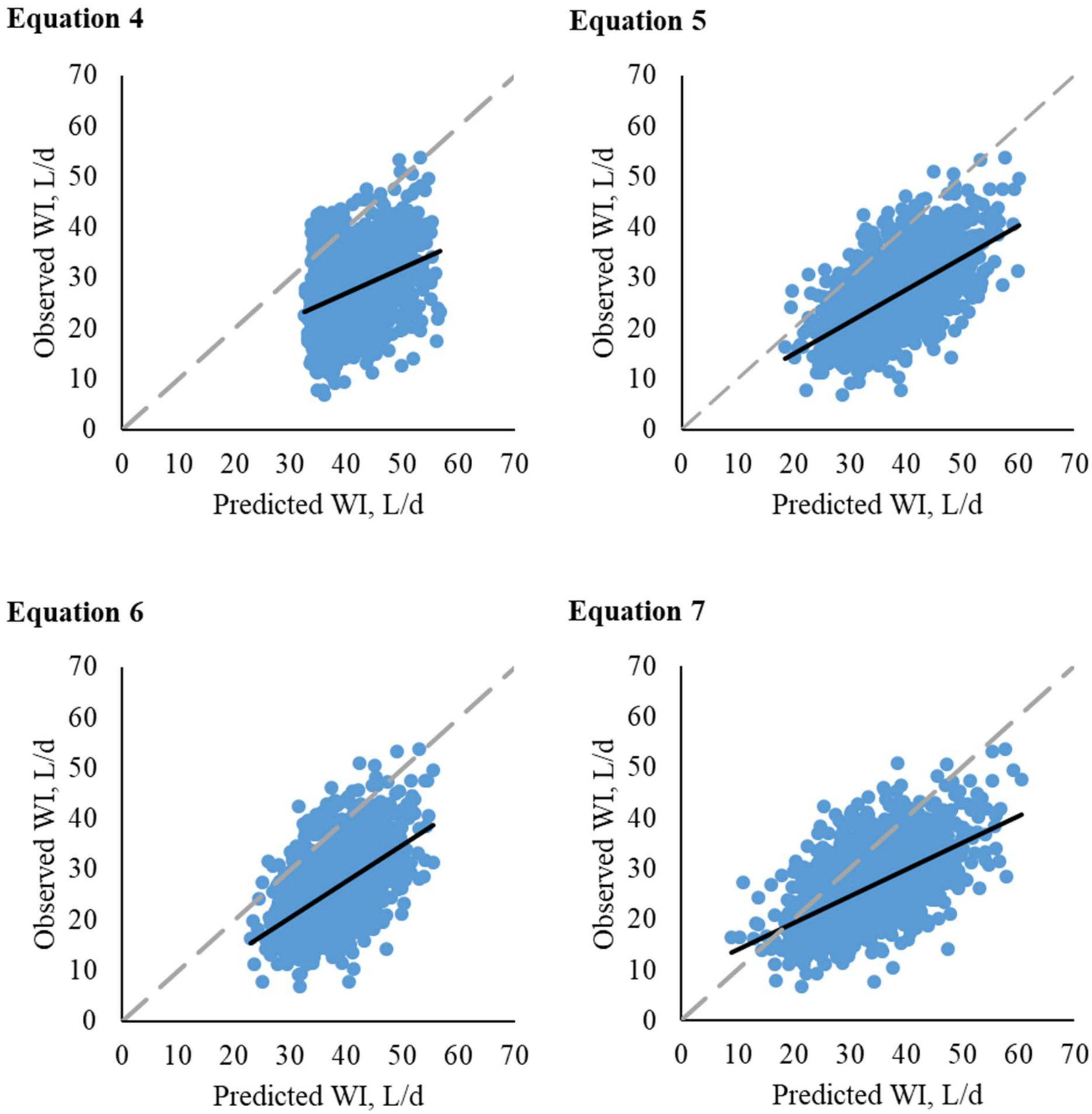


Figure 2.2. Observed vs. predicted individual water intake (WI) plots for finishing (FIN) Angus steers during a 42-d evaluation period. Each panel represents the evaluated equations: Equation 1 = Hicks et al. (1988); Equations 2a (minimum temperature) and 2b (temperature-humidity index) = Arias and Mader (2011); Equations 3 (growing) and 4 (finishing) = NASEM (2016); Equation 5 (combined), 6 (winter), and 7 (*ad libitum*) = Ahlberg et al. (2018). The solid line represents the fit of the regression, and the dashed line represents the equality line.

CHAPTER III

EXAMINING THE INFLUENCE OF SOLAR RADIATION AND DRY MATTER INTAKE ON FINISHING STEER WATER INTAKE PREDICTION EQUATIONS

ABSTRACT

Predicting water intakes (**WI**) for finishing feedlot cattle is crucial to maximize production and manage herd water supply. Most published WI equations include solar radiation (**SR**) and DMI as important predictor variables; however, these variables are not easily attainable for producers. Current equations use absolute WI in L/d as the dependent variable, but water intake as a percent of body weight (**WI%BW**) may serve as a better estimator. Past equations were based on pen WI data for finishing cattle or individual WI data for growing cattle. The objectives of this study were to develop equations with individual finishing steer WI data, to evaluate the effects of excluding SR and DMI on equation development, and to examine the predictive ability of WI vs WI%BW equations. Forty-six Angus steers were placed in an Insentec facility and individual DMI and WI were collected over 51 d. Steers had access to *ad libitum* feed and water and were fed a finishing ration (82% concentrate; 8% roughage). Weather data were obtained from a Mesonet station (3.2 km W of Stillwater, OK). Four WI and 4 WI%BW equations were developed where equations included all possible predictor variables (**OVRL**), DMI without SR (**DMIO**), SR without DMI (**SRO**), or excluded both SR and DMI (**SIMP**). Equations were evaluated with a secondary dataset by regressing observed on predicted WI or WI%BW. During development, the OVRL and DMIO WI and WI%BW equations accounted for greatest variation in intakes and had smallest prediction errors. During evaluation for WI, the OVRL WI equation was the most accurate (intercept = 7.22; slope = 0.91; mean bias = 2.40) but the DMIO WI equation was the most precise (R^2 = 0.67; RMSE = 4.87). For WI%BW, the OVRL WI%BW was the most accurate (intercept = 1.20 and slope = 0.95), and the OVRL, SRO, and SIMP WI%BW equations performed with similar levels of precision. The WI%BW equations generally produced higher R^2, intercepts closer to 0, smaller RMSE, and higher *F*-ratios than the WI equations during equation development. The WI%BW equations predicted intakes with greater precision and accuracy than WI equations, but were more sensitive to inaccurate BW estimates. These results show that it is important to include DMI and SR in models to optimize equation performance, but equations including DMI without SR were viable options to avoid the use of SR values. Additionally, using WI%BW as the dependent variable could improve water intake predictions.

Key words: finishing cattle, Insentec, predictions, water intake (WI), water intake as a percent of body weight (WI%BW)

INTRODUCTION

Water is the most important nutrient for cattle as it is required for body temperature regulation, digestion processes, metabolism, lactation, and reproduction (NASEM, 2016). It is important for producers to predict water intake (**WI**) to ensure proper supplies for health and production of the herd. There have been a variety of WI equations developed for feedlot cattle (Ahlberg et al., 2018a; Arias and Mader, 2011; Hicks et al., 1988; NASEM, 2016) that include different inputs. Common inputs used to predict WI are dry matter intake (**DMI**) and solar radiation (**SR**; Hicks et al., 1988; Arias and Mader, 2011; Ahlberg et al., 2018a); however, these variables are not always available to producers making it difficult to predict WI with current equations. Some equations were developed with pen WI data for cattle fed a finishing diet (Arias and Mader, 2011; Hicks et al., 1988; Sexson et al., 2012) and few were developed with individual WI data for cattle fed a growing diet (Ahlberg et al., 2018a). Water intake in liters per day has been used as the dependent variable in these equations but WI is variable with standard deviations up to 13.1 L/d (Ahlberg et al., 2018a). Many of the WI equations do not account for individual body weights which may account for some of the individual animal variation in WI independent or in place of DMI. Body weight is also much more commonly available than DMI for individual cattle in most production settings. Thus, equations utilizing water intake as a percent of body weight (**WI%BW**) as the dependent variable may enhance the predictive ability of the models for individual animals.

The objectives of this study were to develop equations for finishing steers based on individual data, assess the impacts of DMI and SR on prediction models, and examine the predictive ability of equations using WI%BW compared to WI.

MATERIALS AND METHODS

All procedures were approved by the Oklahoma State University's Institutional Animal Care and Use Committee (ACUP #AG13-18 and #AG12-18).

Equation Development Dataset

On August 21, 2018, forty-eight Angus steers (arrival BW = 431 ± 33 kg) were shipped from Huntsville, Missouri to the Willard Sparks Beef Research Center (**WSBRC**) in Stillwater, Oklahoma (7966 km). Cattle were processed the following morning with vaccinations for respiratory (Titanium 5+ PH-M; Merck Animal Health, Madison, NJ) and clostridial (Vision® 7 with spur; Merck Animal Health) diseases, treated for external and internal parasites (Ivermectin; Noromectin®, Norbrook, Overland Park, KS; Fenbendazole, Safe-guard, Merck Animal Health), and given an estradiol (20 mg) and trenbolone acetate (200 mg) implant (Revalor®-200; Merck Animal Health). Steers were also ear-tagged with an electronic identification (eID) tag in the left ear. Following processing, steers were moved into general holding pens for 7 days where they were fed a common receiving diet.

In late August 2018, steers were placed into the Insentec Roughage Intake Control (**RIC**) (Hokofarm Group, The Netherlands) facility at the WSBRC, and began a 25 d acclimation period to the RIC system. This period was used to allow cattle to acclimate to the new environment and learn to use the RIC system. Two steers were removed from the study due to failure to consume feed or water from the RIC system during acclimation. The RIC facility contained 4 pens (31.85 × 11.27 m each) with 6 feed bunks and 1 water bunk each and had 9.14 × 11.27 m of shade availability. Each water bunk held approximately 47 kg of water and water bunks were cleaned weekly. The remaining 46 steers had access to all 4 pens throughout the study. The RIC system determined individual daily feed and water intakes by recording the weights of feed or water in the bunk as each animal enters and leaves, and then calculated the difference between the beginning and ending feed and water weights.

At the end of the acclimation period, steers began the first step of a 24 d step-up transition to a finishing diet (Table 1). After seven days on the finishing diet a 51 d *ad libitum* feed and water intake period was initiated that lasted from late October to mid-December 2018. Steer full body weights were recorded twelve days prior to the start of the intake period (d -12) and on days 0, 1, 33, 50, and 51.

Days with equipment malfunctions, heavy rain events, missing weather data, or weigh days were removed from the dataset. Rain events were recorded throughout the intake period, and days with thunderstorms or heavy rain were removed to reduce the possibility that animals were consuming water that was not recorded by the RIC system. Two days following a heavy rain event were also removed to allow time for any standing water to dissipate. This selection criterion resulted in 10 days being removed from the dataset. Ahlberg et al. (2018b) found that 42 d is an adequate timeframe to simultaneously collect accurate feed and water intake data. Thus, 42 d were selected from the 51 d intake period to use for equation development and the seventh day (d -1) that steers were consuming the finishing diet was added to the dataset to provide 42 d of intake data.

Each data file was filtered by removing records where bunk visits that were less than 5 seconds in length. Following the removal of these records, total daily feed and water intakes were determined. Daily feed and water intakes that were outside 3 SD of the animal's average daily intake or the herd's average daily intake were removed. This resulted in 1.81% of intakes being removed.

Average daily gain (**ADG**) was calculated by regressing BW collected on d -12 to 0, 1 to 33, and 33 to 51 and used to calculate daily body weights for each steer. Daily water intakes as a percent of body weight (WI%BW) were calculated by dividing daily water intake (L/d) by daily body weight (kg).

Evaluation Dataset

The dataset used for evaluation is described in Maxwell (2014) and Maxwell et al. (2015). Briefly, 27 black-hided, certified-natural steers were placed into the WSBRC Insentec RIC system in April 2013 and fed a conventional finishing diet. The diet contained 47.84% dry-rolled corn, 6.88% switchgrass hay, 14.6.% dried distiller's grains, 15.15% Sweet Bran (Cargill; Dalhart, TX), 10.37% liquid supplement, and 5.17% dry supplement on a dry matter basis (Maxwell, 2015). The dry supplement contained a mixture of ground corn, wheat middlings, vitamins, minerals, Rumensin 90®, and Tylan 40® (Maxwell, 2015). Steers were housed in 2 pens, with 13 or 14 animals/pen, and had access to 6 feed and 1 water bunk per pen. Each pen had 31.9 × 11.3 m of space and 9.2 × 11.3 m of shade availability. Individual feed and water intakes were collected over a 91 d period before zilpaterol hydrochloride was added to the diet (Maxwell, 2014). Steers were weighed on d -1, 0, 28, 56, and 91. Average daily gain was calculated by regressing body weight between days 0 to 28, 28 to 56, and 56 to 91. Daily body weights and WI%BW were calculated in the same manner as the development dataset.

Data was sorted and 42 d were selected using the same criteria as the development dataset; however, rain was not considered a factor when selecting days for evaluation because days with high amounts of rainfall, which could lead to standing water in the pens, were not recorded throughout that study. Water intakes were not measured until after June 2, 2013 due to system malfunctions as reported in Maxwell (2014). Days considered for selection to be included in the evaluation period did not begin until after that date and ended prior to the addition of zilpaterol hydrochloride (Zilmax®; Merck Animal Health). The final days selected for evaluation spanned from mid-June to early August 2013. After selecting the 42 d evaluation data, daily individual feed and water intakes outside 3 SD were removed resulting in 1.76% of the daily data being removed.

Weather Variables

Daily weather data was obtained from the Oklahoma Mesonet Station tower located 3.2 km west of Stillwater (http://weather.ok.gov/index.php/sites/site_description/stil). Weather variables included average daily temperature (**TAVG**), minimum daily temperature (**TMIN**), maximum daily temperature (**TMAX**), average daily relative humidity (**HAVG**), average daily wind speed (**WS**), and total daily solar radiation (**SR**). Temperature-humidity index (**THI**) was calculated based on the equation in Arias and Mader (2011) using TAVG and HAVG. The Mesonet station transmits data for each variable every 15 minutes (Brock et al., 1995). Wind speed was collected with a R.M. Young model 5103 wind sensor that is located 2 m above ground (Brock et al., 1995). Relative humidity and temperature data were measured with a thermistor-sorption probe that is mounted 1.5 m off the ground (Brock et al., 1995). Solar radiation was measured at 1.75 m above ground with a silicon photodiode-type pyranometer that is mounted to a tripod near the tower (Brock et al., 1995).

Statistical Analysis

Summary statistics were obtained using the MEANS procedure of SAS 9.4 (SAS Inst. Inc., Cary, NC), and calculated using individual daily steer WI, WI%BW, DMI, and BW. Since animal data (DMI, WI, WI%BW, and BW) was different for each day while weather data remained constant, animal data were averaged per day prior to use in equation development and equation evaluation to prevent biasing the output results for each weather variable that would occur if the data were analyzed on an individual animal basis.

Pearson correlation coefficients (**r**) were calculated using the CORR procedure of SAS to determine the relationship between independent and dependent variables, and r values were considered significant at $P < 0.05$. Pearson correlation coefficients were computed based on daily weather variables and average daily steer WI, WI%BW, DMI, and BW.

Equation Development. Linear and quadratic variables examined for model development were TAVG, TMIN, TMAX, HAVG, SR, THI, WS, DMI, and BW. Rain was not included as a predictor variable since days with heavy rain events were excluded from the dataset as part of the selection criterion. Additionally, BW was not included as a possible predictor variable in the WI%BW equations as it was already accounted for in the WI%BW calculations. When comparing *r* values between independent variables, TAVG had $r > 0.80$ with TMAX and TMIN which suggested those variables were strongly related. Thus, TMAX and TMIN were not included in models that contained TAVG as that would have introduced multicollinearity into the model.

Water intake and WI%BW equations were developed using PROC REG in SAS. Forward, backward, maxR, and stepwise regression methods were performed to determine the best method for model development. Coefficient of determination (**R^2**), root mean square error (**RMSE**), *F*-ratios (***F***), and semi-partial R^2 were obtained. Variance inflation factors (**VIF**) and heteroscedasticity-consistent standard errors (**HCC**) were calculated during regressions to evaluate issues with multicollinearity and heteroscedasticity, respectively. Models with VIF ≥ 10 were determined to have multicollinearity and were not considered for final model selection. Models with HCC *P*-values < 0.05 were considered homoscedastic and accepted as potential final models (SAS, 2019b). A Durbin-Watson test for autocorrelation was performed in the REG procedures of SAS (SAS, 2019a). Models with a *P*-value > 0.05 were determined to have no autocorrelation and were considered for final model selection. In order, final models were selected based on the highest R^2, lowest RMSE, largest *F*-ratio, smallest difference between model degrees of freedom and Mallow's C_p statistic, and smallest intercept.

Four WI and four WI%BW finishing equations were developed as follows: 1) Overall equation (**OVRL WI; OVRL WI%BW)** including linear or quadratic DMI and SR, 2) DMI only (**DMIO WI; DMIO WI%BW**) equation including DMI or DMI squared, but excluding SR and SR squared, 3) SR Only (**SRO WI; SRO WI%BW**) equation including SR or SR squared, but excluding DMI and DMI squared, and 4) simplistic (**SIMP WI; SIMP WI%BW**) equation excluding linear and quadratic DMI and SR. The equations were developed in this manner to evaluate the impact of excluding DMI and SR on the predictive ability of the equations and to compare WI versus WI%BW equations. The developed finishing equations only account for free water intake and do not include water consumed from feed. The DMIO WI equation was developed using the forward selection method in SAS. Each variable that entered the model had a significant *F*-ratio at $P \leq 0.05$. The forward method begins by adding the variable with the largest *F*-ratio that meets the entry criteria and continues to add variables in this manner until all variables in the final model are significant. The remaining 7 finishing equations were developed using the backward selection method of SAS. Variables that remained in the model had a significant *F*-ratio at $P \leq 0.05$. The backward method starts with all variables in the model and removes the variable with the least significant *F*-ratio. This process continues until all variables remaining in the model have significant *F*-ratios.

Four of the final models had HCC *P*-values > 0.05. The OVRL WI model was slightly heteroscedastic with $P = 0.069$ for BW. The DMIO WI equation was slightly heteroscedastic with $P = 0.060$ for DMI squared. The SIMP WI equation was heteroscedastic with $P = 0.170$ for HAVG. The DMIO WI%BW equation was heteroscedastic with $P = 0.053$ for DMI and $P = 0.111$ for TMIN squared. Homoscedasticity refers to an equal variance in the residuals of the prediction model (Field and Miles, 2010), and significant heteroscedasticity can bias the standard errors and test statistics (Williams, 2015). Due to the substantial variability reported for steer water intakes, the OVRL WI, DMIO WI, SIMP WI, and DMIO WI%BW models were still accepted as final models.

Equation Evaluation. Predicted WI or WI%BW were calculated for each new finishing equation and observed WI or WI%BW were regressed on predicted WI or WI%BW using PROC REG in SAS. Tedeschi (2006) explained that intercept and slope can be used to evaluate equation accuracy while R^2 can be used to examine equation precision. Thus, intercept, slope, and R^2 were obtained from the regressions. Root mean square error was also obtained to evaluate model precision (Anele et al., 2014). These variables were chosen to evaluate the equations similar to previous publications (Galyean et al., 2011; Anele et al., 2014; Zanetti et al., 2019).

Shah and Murphy (2006) described that mean and linear biases are commonly used to evaluate regression models, and these statistics test model robustness and model inadequacy, respectively. Mean and linear biases were calculated for WI and WI%BW based on St-Pierre (2003) by regressing residual predicted (observed - predicted) on mean-centered predicted (predicted - average predicted) values. The mean bias was the intercept from the mean-centered regression and the *P*-value was obtained from performing a t-test to determine if the intercept was equal to 0. If $P < 0.05$, the mean bias was significantly different from 0. The linear bias was the slope of the mean-centered regression. A t-test was performed in SAS to determine if the slope was equal to 1. If $P < 0.05$, the linear bias was significantly different from 1.

RESULTS AND DISCUSSION

Animal and Environmental Variables

Summary statistics of daily individual steer WI, WI%BW, DMI, BW, and weather variables for equation development and evaluation are reported in Tables 3.2 and 3.7, respectively. Relationships between outcome and predictor variables are presented in Tables 3.3 and 3.4. Data for THI was not included in these tables since THI did not remain in any of the final prediction models.

The equation development data was collected over the winter months; whereas, the equation evaluation data was obtained during the summer. Thus, all daily average environmental variables were lower during the equation development period (Table 3.2) than the equation evaluation period (Table 3.7), except for HAVG being 2.35% higher during development. Average daily temperature (TAVG), TMIN, TMAX, and WS were more variable during equation development (SD = 5.86 vs. 2.80, 5.67 vs. 3.20, 7.31 vs. 2.95, and 4.78 vs. 3.09, respectively). Total daily solar radiation (SR) and HAVG were more variable in the evaluation dataset (SD = 6.42 and 10.61, respectively) than the development dataset (SD = 4.70 and 9.66, respectively).

Individual steer WI and WI%BW were more variable during equation evaluation (SD = 17.2 L/d and 3.5%) than development (SD = 6.7 L/d and 1.2%) (Tables 3.2 and 3.7). Adjusting water intakes using BW did not reduce the variability of intakes during equation development (WI CV% = 25.2; WI%BW CV% = 25.5) or evaluation (WI CV% = 31.2; WI%BW CV% = 31.5). Daily DMI was similar between the 2 datasets with steers consuming an average of 1 kg/d more feed during the equation development period. Dry matter intake was more variable during development (SD = 2.6 kg/d) than evaluation (SD = 1.6 kg/d). The small difference in DMI between the datasets was likely due to cattle consuming more feed to regulate body temperature through metabolic heat production during the winter (NASEM, 2016). Average beginning and ending steer body weights were higher (531 and 616 kg, respectively) and more variable (SD = 47 and 50 kg, respectively) in the equation development dataset. Average daily WI and WI%BW were approximately 2.1 and 2.4 times higher during the equation evaluation period than the development period, respectively. This data follows the same trend as other studies which showed that cattle consumed more water during the summer than winter (Sexson et al., 2012; Ahlberg et al., 2018a). Additionally, Holter and Urban (1992) found a curvilinear effect of season on WI of lactating Holstein cows with greatest intakes in June and lowest in December. These results were expected as animals must increase water consumption to account for higher water losses due to evaporative cooling and panting (Beade and Collier, 1986; Berman, 2006) during times of heat stress.

All predictor variables were significantly ($P < 0.05$) correlated to WI except for DMI, DMI^2, and $TMIN^2$ (Tables 3.3 and 3.4). All predictor variables were significantly correlated to WI%BW ($P < 0.05$), except for DMI, HAVG, DMI^2, $TMIN^2$, and $HAVG^2$. Moderately strong correlations were observed between WI and TMAX (0.769), TAVG (0.665), SR (0.642), $TMAX^2$ (0.803), $TAVG^2$ (0.669), and SR^2 (0.631). A similar trend was observed with WI%BW being highly correlated to TMAX (0.811), TAVG (0.764), $TMAX^2$ (0.845), and $TAVG^2$ (0.776) and moderately correlated to SR (0.602) and SR^2 (0.613). These results suggest that TMAX, TAVG, and SR are important factors for predicting water intake for finishing feedlot steers in the winter, and excluding SR from the prediction models could have negative effects. In a univariate analysis during the winter, Arias and Mader (2011) reported highest R^2 values between WI and maximum temperature (0.07), relative humidity ($R^2 = 0.07$), and temperature-humidity index ($R^2 = 0.05$); whereas, solar radiation and DMI accounted for only 3% and 2% of the variation in WI, respectively. Solar radiation became a more important predictor variable in the summer ($R^2 = 0.14$) and overall ($R^2 = 0.47$) univariate analyses. The R^2 value for SR in the summer was low but was the highest R^2 associated with any variable in that univariate analysis. Maximum, minimum, and mean temperatures and temperature-humidity index had the highest R^2 (0.54, 0.56, 0.57, 0.57, respectively) associated with WI across seasons. In a univariate analysis, Ahlberg et al.

(2018a) reported that DMI (R^2 = 0.29) and mid-metabolic body weights (R^2 = 0.20) were the most important predictors of WI for growing steers in the winter, but that TAVG (R^2 = 0.20) and DMI (R^2 = 0.16) were the most important predictors in the summer. These authors also noted that mid-metabolic body weights, TAVG, and SR had the highest correlation coefficients (R^2 = 0.14, 0.26, 0.22) associated with WI when cattle were fed *ad libitum*. In order of importance, Ahlberg et al. (2018a) also explained that SR, TAVG, RH, and WS were the most important predictors of WI%BW when examined as single-factor models. Since cattle were fed *ad libitum* during the winter in the equation development dataset, it was not surprising that TAVG, TMAX, and SR were highly correlated with WI and WI%BW in this study. Holter and Urban (1992) found a significant moderate correlation between free water intake and DMI for dry (r = 0.52) and lactating (r = 0.64) Holstein cows. Sexson et al. (2012) described a positive relationship between WI and DMI in their univariate analysis but noted that the relationship between DMI and WI can be inconsistent because DMI tends to increase in the winter and decrease in the summer, while WI has the opposite trend. Thus, the small negative correlation coefficient between WI or WI%BW and DMI or DMI^2 for feedlot steers fed during the winter was not surprising.

Impact of SR and DMI on Water Intake Equations

Regression analysis results from 8 developed finishing WI and WI%BW equations including both SR and DMI (**OVRL**), only DMI (**DMIO**), only SR (**SRO**), or excluding both SR and DMI (**SIMP**) are reported in Table 3.5. Partial correlation coefficients associated with each variable for each equation are presented in Table 3.6.

Allowing linear or quadratic DMI and SR to enter the model (OVRL) improved the WI and WI%BW prediction equations. The OVRL WI and WI%BW models accounted for the highest amount of variation in water consumption (R^2 = 0.933 and 0.944, respectively) and had the lowest SD of the residuals (RMSE = 1.007 and 0.185, respectively) compared to equations without DMI, SR, or both. Additionally, the OVRL WI%BW equation had the highest *F*-ratio (97.58) and intercept closest to zero (0.720) compared to other WI%BW models. As DMI, SR, or both were removed as possible predictor variables, the equations became more simplified in that fewer other animal and environmental variables entered or remained in the model. This simplification occurred because DMI and SR^2 accounted for a total of 19.9% and 15.9% of the variation in water intake in the OVRL WI and WI%BW models, respectively (Table 3.6). Thus, there were fewer variables remaining in the DMIO, SRO, or SIMP models that could adequately improve the water intake equations.

Arias and Mader (2011) developed predictions equations that included DMI and SR based on data from steers and heifers finishing in the summer and winter. In addition, the 2 equations either included THI or TMIN. The THI equation had a R^2 of 0.65 while DMI and SR contributed 2% and 6% of the variability explained by the equation, respectively. Whereas, the equation with TMIN had a R^2 of 0.65 while DMI and SR contributed 2% and 7%, respectively. These R^2 were possibly smaller than the OVRL equations in this experiment because the proposed equations utilized average daily herd WI, WI%BW, DMI, and BW while Arias and Mader (2011) used individual animal daily water intakes. The partial R^2 for DMI was higher in the OVRL WI equation (0.054) but lower in the WI%BW equation (0.005) compared to Arias and Mader (2011). The lower partial R^2 for DMI in the WI%BW OVRL equation may be related to the significant ($P < 0.01$) moderate correlation between DMI and BW (0.469; Table 3.3). Most of the variation in water consumption explained by DMI was likely removed when BW was accounted for in the WI%BW calculations. The partial R^2 values for SR in the proposed OVRL equations (WI = 0.145; WI%BW = 0.154) were higher than in the Arias and Mader (2011) equations. This difference was surprising since cattle in this study had access to shade. However, Ahlberg et al.

(2018a) developed prediction equations for growing steers that also had access to shade. In those models, SR accounted for less than 1% of the variation and DMI accounted for 5 to 29% of the variation in WI. The partial R^2 tended to be higher and lower for SR and DMI, respectively, in the OVRL WI and WI%BW equations than those reported in Ahlberg et al. (2018). The smaller partial R^2 for DMI was likely a result of averaging the herd's daily DMI during equation development in this study which would have removed some of the individual variation in DMI associated with WI and WI%BW.

When comparing models within a dependent variable that included only DMI, only SR, or neither, the DMIO models produced better regression statistics. The DMIO WI%BW equation had the highest R^2 (0.890), lowest RMSE (0.255), and an intercept (1.960) closest to 0. Similarly, the DMIO WI equation had the highest R^2 (0.889), lowest RMSE (1.220), and the highest *F*-ratio (74.27). Maximum temperature squared was a major predictor variable for the DMIO WI (partial R^2 = 0.537) and WI%BW (partial R^2 = 0.496) models while DMI^2 (WI partial R^2 = 0.055) or DMI (WI%BW partial R^2 = 0.005) accounted for only a small portion of the variation in water consumption. The addition of DMI^2 in the DMIO WI equation increased the model R^2 by 0.055 (Table 3.6). This resulted in a 0.035 L increase in daily WI for every kilogram of daily DMI^2 (Table 3.5). When inserting the average daily DMI from Table 3.2 into the 0.035 * DMI^2 portion of the equation, daily WI increased by 5.3 L. The difference between the intercept for the DMIO WI equation (23.560) and the intercept for the SIMP WI equation (29.156) is approximately 5.6 L. Thus, the lower R^2 values and increased intercept for the SIMP WI equation are a result of excluding DMI^2 from the model. Since DMI can be more easily obtained in a feedlot, these results indicate that the DMIO equations are a viable option for feedlot managers to utilize when SR values are not available.

Dry matter intake has been an important predictor for WI in various studies even when SR was not included in the models (Winchester and Morris, 1956; Murphy et al., 1983; Hicks et al., 1988; Holter and Urban, 1992; Appuhamy, et al., 2016; Zanetti et al., 2019). The slope estimates for DMI^2 (0.035) in the WI or DMI (0.176) in the WI%BW DMIO models were smaller than those presented in the literature, which ranged from 0.30 (Appuhamy et al., 2016) to 2.47 (Holter and Urban, 1992) for DMI, suggesting that DMI has a smaller influence on the developed WI predictions when SR is included.

The SRO WI model had the lowest R^2 (0.787), highest RMSE (1.694), and lowest *F*-ratio (34.09) of all WI models, which suggests that there are variables missing that could improve the fit of the model (Table 3.5). However, the intercept (4.565) for this equation was closest to 0 out of all proposed WI equations. These results suggest that the SRO WI equation was the least viable option to utilize when predicting WI for finishing steers. So, even if a producer had access to SR but not DMI, the SIMP WI equation may be a better model to predict WI than the SRO equation. The SRO WI%BW equation showed slightly different results because it had a higher R^2 (0.861), lower RSME (0.283), and lower intercept (4.151) than the SIMP WI%BW equation. The SRO WI%BW equation had the lowest *F*-ratio (57.11) of all proposed WI%BW equations, which was only 1.35 units smaller than the DMIO WI%BW equation.

The SRO WI and WI%BW regression statistics show that removing DMI from the model decreases equation performance to a greater extent than removing SR. The variables with the highest partial R^2 in the SRO WI equation were TAVG (0.442) and WS (0.237); whereas, SR had a partial R^2 value of 0.086 (Table 3.6). In the SRO WI%BW equation, $TMAX^2$ and TMIN have the highest partial R^2 (0.463 and 0.253, respectively) while SR had the lowest partial R^2 (0.022). These results show that although SR explained some of the variation in water consumption, it is not the most important variable even when DMI was excluded from the model. Since the relationship between DMI and WI has been reported to be inconsistent (Sexson et al., 2012), it was surprising that the DMIO models yielded more favorable regression statistics than the SRO models. The greater impact that excluding DMI from the model had on the WI and WI%BW equations compared to excluding SR may be because cattle had access to shade in this study and water consumption was measured over the winter when SR would have a lesser impact on WI than it would during the summer when heat stress becomes problematic.

The SIMP equations have the smaller number of variables included in the models. Both SIMP equations include $TMAX^2$ and WS^2 and the SIMP WI equation also includes HAVG. Although the inclusion of SR and DMI have been shown to improve the prediction models, the WI and WI%BW SIMP equations still have relatively high R^2 (0.835 and 0.825, respectively), low RMSE (1.471 and 0.309, respectively), and high *F*-ratios (63.97 and 92.05). Additionally, the R^2 for the SIMP equations were higher compared to published equations (0.7361, Hicks et al., 1988; 0.65, Arias and Mader, 2011; 0.32, Sexson et al., 2012; 0.34 to 0.41, Ahlberg et al., 2018) likely because herd feed and water intakes were averaged by day prior to equation development in this experiment. The intercept for the SIMP WI equation (29.156) was substantially higher than those in the OVRL WI (-7.144) and SRO WI (0.451) equations, while the intercept for the SIMP WI%BW equation (4.263) was only slightly higher than other WI%BW equations. The higher intercepts for the SIMP equations show that there was bias introduced into the equations when both SR and DMI were excluded, and that this bias was greater in the WI equations. These results show that SR and DMI are beneficial when predicting water intake for finishing feedlot steers, but reasonable estimates may be generated with the simplified equations.

Comparison of WI vs. WI%BW Equations

When comparing each WI equation to its WI%BW counterpart (i.e. OVRL WI vs OVRL WI%BW), all WI%BW equations resulted in the lowest RMSE and intercepts closest to 0, which indicates that the WI%BW equations resulted in lower prediction errors. The WI%BW equations also had higher R^2 and larger *F*-ratios except the SIMP WI equation which had a R^2 that was 0.01 greater than the SIMP WI%BW equation and the DMIO WI equation had an *F*-ratio that was 15.81 larger than the DMIO WI%BW equation. In addition, body weight described 12.7% and 2.1% of the variation in WI in the OVRL and SRO WI equations. Although BW was not included in the DMIO or SIMP WI equations, the variation in WI (SD = 6.7; range = 46.9) was greater than the variation in WI%BW (SD = 1.2; range = 9.3) in the development dataset (Table 3.2). This variation in WI could explain why the WI%BW equations produced more favorable regression statistics even when BW was not included in the WI model. This data suggests that utilizing WI%BW as the dependent variable for finishing steer prediction equations can improve the fit of the models even in instances where DMI, SR, or both are excluded from the equations. There have been no other studies that developed water intake equations utilizing WI%BW as the dependent variable to compare to these results.

A limitation to the WI%BW equations is that producers must be able to collect accurate and regular body weights for their cattle. If body weights are not collected consistently, water consumption may be greatly under or over predicted leading to water deficiencies for the herd or water losses at the facility. Cattle that have restricted access to water have been found to have decreased performance (Marques et al., 2012) which lead to economic losses over time. Oversupplying water can also have negative economic impacts if water is wasted due to evaporation, spillage, or fecal contamination when cattle do not consume all supplied water. Thus, caution should be taken when choosing to use the WI%BW equations. The same warning could be suggested for the OVRL WI and SRO WI equations as they include body weight as a predictor variable, but with a lower impact. For instance, assume the actual average body weight of a group of 500 steers is 550 kg, but it was estimated to be 500 kg. If a WI%BW equation predicts that each steer will drink 10% of their body weight on average, the actual water intake would be 27,500 L/d for the group; whereas, water consumption calculated based on the estimated body weight would be 25,000 L/d for the group. This shows that a WI%BW equation would under estimate the herd water intake by 2,500 L/d. When predicting WI using only the coefficient for BW from the OVRL WI equation, the actual WI associated with BW would be ~7,975 L/d for the herd. The WI calculated based on the estimated BW would be 7,250 L/d for the herd. Thus, the OVRL WI equation would have under estimated the herd water intake by only 725 L/d. So, the WI%BW equations may be more sensitive to inaccuracies in body weight records than the WI equations.

Evaluating Finishing Prediction Equations

Evaluating the accuracy and precision of the developed equations using an independent dataset is important to examine the predictive ability of the equations when applied to different scenarios. Evaluation results from the observed versus predicted WI and WI%BW regressions are presented in Table 3.8 and can be visualized in Figure 3.1 for WI and Figure 3.2 for WI%BW.

Examining the accuracy of developed equations is essential to determine if the equations predicted water consumption close to the observed intakes. The intercepts were closest to 0 and slopes were closest to 1 for the DMIO (intercept = -0.61; slope = 1.28) and OVRL (intercept = 1.20; slope = 0.95) WI%BW equations. The OVRL WI equation predicted WI with highest accuracy (intercept = 7.22; slope = 0.91) out of all WI equations. Additionally, the SIMP WI (intercept = -41.08; slope = 2.64) and WI%BW (intercept = -6.93; slope = 2.52) equations were the most inaccurate equations. These results emphasize that DMI was an important factor to accurately predict WI%BW or WI for feedlot steers and that excluding both DMI and SR negatively impacted the accuracy of the equations. Interestingly, the magnitude of the increase in intercepts was more drastic for the WI equations when DMI, SR, or both were excluded from the model. The DMIO, SRO, and SIMP equations had markedly larger intercepts (-32.83, -32.44, -41.08, respectively) than the OVRL WI equation (7.22). Intercepts become higher as models accumulate bias, which occurs when there are missing variables that could improve the fit of the model. Thus, these results show that including both DMI and SR in the equations was crucial to predict WI accurately.

The extent to which the slopes and intercepts changed with the exclusion of SR (DMIO), DMI (SRO), or both (SIMP) can be more easily examined in Figures 3.1 and 3.2. Unsurprisingly, the equations that were most in line with the equality lines were the OVRL WI and WI%BW equations. As the slopes became steeper and intercepts became farther from 0 for the DMIO, SRO, and SIMP WI and WI%BW equations, the regression lines gradually became more perpendicular to the x-axis. The shift in regression lines means that the equations excluding DMI, SR, or both were only able to predict a narrower range of WI or WI%BW than the observed values. The narrowing in predictive ability would have a greater impact on the WI equations as WI was more variable than WI%BW. The OVRL WI equation was able to predict the widest range (~28 L/d) in WI beginning at ~35 L/d and ending at ~64 L/d (Figure 3.1). In comparison, the DMIO, SRO, and SIMP WI equations were able to predict WI ranges of ~13, 11, and 12 L/d, respectively. The OVRL WI%BW equation was also able to predict the largest range in WI%BW (~6%) with a minimum of ~7% up to ~13% (Figure 3.2). The DMIO, SRO, and SIMP WI%BW equations predicted intakes with a range of ~3% each. This decrease in ranges of predicted intakes when equations excluded SR, DMI, or both makes it more difficult to accurately predict intakes for a group of feedlot cattle when producers do not have access to data for those variables.

The mean biases for all proposed equations were significant ($P < 0.01$) and positive meaning that all equations under predicted observed water consumption (Table 3.8). This was expected as the equation development dataset was collected over the winter (Table 3.2) when intakes were more than 50% lower than those obtained in the evaluation dataset collected over the summer (Table 3.7). However, the mean biases were smaller for all WI%BW equations which shows that those equations predicted water consumption closer to the observed values than its WI counterparts. As expected, the OVRL WI and WI%BW equations predicted intakes closest to the observed values (mean bias = 2.40 and 0.69, respectively) which reiterates that DMI and SR are important predictors of water consumption. Additionally, the OVRL WI and WI%BW equations had significant ($P < 0.0001$), negative linear biases (-0.09 and -0.05, respectively) meaning that the magnitude of under prediction decreased as WI or WI%BW increased. This can be visualized in the OVRL panels of Figures 3.1 and 3.2 where the predicted intakes became closer to the equality line as the predictions increased. Of the remaining equations, the DMIO WI and WI%BW equations under predicted intakes by the smallest margin (mean bias = 18.02 and 1.96, respectively) followed by the SRO (mean bias = 18.32 and 3.24, respectively) and SIMP (mean bias = 18.75 and 3.97, respectively) equations. Excluding SR, DMI, or both from the models had a seemingly greater influence on the predictive ability of the WI equations. The DMIO, SRO, and SIMP WI equations under predicted water consumption by more than 18 L; whereas, the WI%BW equations under predicted water consumption by less than 4% of steer body weight. However, the level of under prediction for the WI%BW equations could amount to ~20 L/d for a 500 kg steer for the SRO and SIMP equations or ~10 L/d for the DMIO equation. The extent to which the SRO and SIMP equations under predicted water consumption were not considerably different between WI or WI%BW equations. The SIMP WI and DMIO WI%BW equations had significant ($P < 0.05$), positive linear biases (1.64 and 0.28, respectively) meaning that the magnitude of under prediction increased as WI or WI%BW increased. This can be examined in the SIMP panel of Figure 3.1 and DMIO panel of Figure 3.2 where datapoints deviated further from the equality line as the WI predictions increased.

It is important to examine model precision as it shows how tightly grouped a set of predictions were for the proposed equations. Since WI was more variable than WI%BW in the development and evaluation datasets, it was expected that the WI equations would be less precise than the WI%BW equations. This trend was observed with the WI%BW equations having lower RMSE than the WI equations. When evaluating the R^2 of the WI vs WI%BW models, all WI equations had higher R^2 than its WI%BW counterpart except for the SRO WI%BW equation which had a R^2 that was 0.07 higher than the SRO WI equation. However, the differences were relatively small with the OVRL and SIMP WI equations having a R^2 that was 0.02 and 0.05 higher than the WI%BW counterparts, respectively. The greatest difference in R^2 was observed when comparing the DMIO equations where the WI equation accounted for 16% more of the variation in water consumption than the WI%BW equation. This large difference in R^2 can be easily visualized in Figures 3.1 and 3.2 where the spread of data points was greater for the DMIO WI%BW equation (Figure 3.2) than the DMIO WI equation (Figure 3.1). These results indicate that most WI equations captured a greater percentage of variation in water consumption than the WI%BW equations, but that predicting water intake as a percent of body weight resulted in smaller prediction errors. Thus, WI and WI%BW equations can predict water consumption with moderate precision.

When examining the impact of SR and DMI on the precision of the prediction equations, the WI and WI%BW equations showed slightly different results that can be visualized in Figure

3.1 for WI equations and Figure 3.2 for WI%BW equations. Equations that predicted water consumption with higher levels of precision resulted in datapoints that are more tightly grouped. The WI equations listed in order of highest to lowest precision were DMIO (R^2 = 0.67; RMSE = 4.87), SIMP (R^2 = 0.64; RMSE = 5.08), OVRL (R^2 = 0.60; RMSE = 5.40), and SRO (R^2 = 0.50; RMSE = 6.01). These results indicate that WI could be predicted with greater precision when DMI was included in the model without SR (DMIO). Additionally, WI could be predicted with a similarly high level of precision when both DMI and SR were excluded from the model (SIMP). These results are similar to Appuhamy et al. (2016) which noted that including DMI in WI equations improved precision of the models when tested with an independent dataset. The exclusion of SR, DMI, or both had a smaller impact on the precision of the WI%BW equations. The SIMP, OVRL, and SRO WI%BW equations predicted water consumption with similar levels of precision in that the R^2 (0.59, 0.58, 0.57, respectively) and RMSE (1.16, 1.18, 1.19, respectively) were not substantially different from each other. These slight differences would likely not have significant impacts on the predicted WI%BW for a herd. The DMIO WI%BW equation accounted for the smallest amount of variation in WI%BW (R^2 = 0.51) and resulted in the highest prediction errors (RMSE = 1.27). Thus, including DMI and SR in the model, including SR without DMI in the model, or excluding both DMI and SR from the model could allow producers to make precise WI%BW predictions.

The evaluation analyses suggest that the best equations to accurately and precisely predict WI or WI%BW were those that included both SR and DMI, and the next best options were equations that included DMI without SR. Since DMI is more easily attainable in feedlots, these equations may be the most viable option for producers when SR is not available. The SRO equations may be used in instances where DMI is unobtainable; however, the SIMP equations had poor performance and should only be used if no other options are available.

CONCLUSION

Finishing WI and WI%BW prediction equations were developed, the impact of SR and DMI on these equations were examined, and the finishing equations were evaluated with an independent dataset. Linear and quadratic forms of TMAX, TAVG, and SR had the highest correlations with WI and WI%BW, but dry matter intake was not significantly correlated to water consumption.

All models explained a large proportion of the variation in intakes with R^2 ranging from 0.787 to 0.944. The most important predictor variables were $TMAX^2$ or TAVG while DMI and SR accounted for relatively small amounts of the variations in WI or WI%BW. In addition, all equations under predicted water intakes when evaluated with an independent dataset potentially because the equations were developed with winter data, while the evaluation dataset was collected over the summer. However, equations that included DMI and SR predicted WI or WI%BW with high levels of precision and accuracy during equation evaluation. These equations also accounted for more of the variation in intakes and had smallest prediction errors during equation development. Thus, DMI and SR should still be included in water intake prediction models, and equations including both variables could help producers manage their water supply efficiently even during the summer. Equations that included DMI without SR were the second-best prediction equations, and equations that excluded both SR and DMI had poorest performance during evaluation. Therefore, the inclusion of only DMI was more important to develop more accurate and precise equations than when only SR was included.

Unlike the national weather data, the Mesonet website has SR data available which allows producers to use water intake equations that include SR. On the other hand, a reasonably priced on-site weather station that includes SR may be of value for producers to generate high quality predictions when accuracy is needed.

The developed WI%BW equations tended to account for more variation in intakes and resulted in smaller prediction errors, better model fit, and smaller intercepts than the WI equations. The WI%BW equations also predicted intakes with greater precision and accuracy during equation evaluation. Predicting water consumption using WI%BW could enable producers to maximize water usage in their operations through more efficient water management. However, the WI%BW equations should only be utilized when cattle body weights are known with reasonable accuracy.

Since heat stress is a major problem in feedlots and water intake is higher over the summer months, the impact of SR and DMI on water intake equations should be explored with equations developed using a dataset collected on cattle finished in the summer. The proposed equations should also be evaluated with data from a variety of locations and from cattle of different sizes and breed compositions to determine equation performance across numerous scenarios.

LITERATURE CITED

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Table 3.1. Diet composition for Angus steers during the 51-d intake period

Item	Amount
Ingredient, % DM	
Dry rolled corn	62.0
Sweet Bran[1]	20.0
Prairie hay	8.0
Dry supplement[2]	5.0
Liquid supplement[3]	5.0
Nutrient Analysis, DM basis[4]	
DM, %	75.6
CP, %	13.6
ADF, %	10.9
TDN, %	87.1
NEm, Mcal/kg	2.16
NEg, Mcal/kg	1.48
Ca, %	0.513
P, %	0.517
Mg, %	0.234
K, %	0.917

[1]Wet corn gluten feed (Cargill, Dalhart, TX).

[2]Dry supplement was composed of 42.6% ground corn, 27.1% calcium carbonate, 20.6% wheat midds, 0.49% magnesium oxide, 0.92% salt, 6.5% urea, 0.12% copper sulfate, 0.15% manganese oxide, 0.08% selenium, 0.47% zinc sulfate, 0.29% Vitamin A, 0.09% Vitamin E, 0.008% Vitamin D, 0.30% Rumensin-90, and 0.19% Tylan-40.

[3]Liquid supplement was primarily composed of 45.9% corn steep, 36.2% cane molasses, 6% hydrolyzed vegetable oil, 5.2% water, 1.2% urea, and 0.1% xanthan gum.

[4]Nutrient analyses were conducted by wet chemistry at a commercial laboratory (Servi-Tech Laboratories, Dodge City, KS).

Table 3.2. Summary statistics for daily individual steer and weather variables used in development of finishing water intake equations[1]

Variable[2]	Mean	SD	CV%	Minimum	Maximum
Animal[3]					
WI, L/d	26.6	6.7	25.2	6.8	53.7
WI%BW[4]	4.7	1.2	25.5	1.2	10.5
DMI, kg/d	12.3	2.6	21.1	3.5	20.8
Beginning BW[5], kg	531	47	8.9	393	613
Ending BW[5], kg	616	50	8.1	505	714
Weather[3]					
TAVG, °C	6.33	5.86	92.6	-4.63	18.03
TMIN, °C	0.24	5.67	2362.5	-9.79	11.24
TMAX, °C	13.28	7.31	55.0	0.43	28.20
HAVG, %	69.31	9.66	13.9	48.09	96.07
WS, km/h	10.30	4.78	46.4	2.01	23.74
SR, MJ/m^2	9.63	4.70	48.8	1.39	15.73

[1]Intakes outside 3 SD of individual animal's daily intakes or the herd's daily intakes were removed.
[2]WI = daily water intake; WI%BW = water intake as a percent of body weight; DMI = daily dry matter intake; BW = body weight; TAVG = average daily ambient temperature; TMIN = minimum daily temperature; TMAX = maximum daily temperature; HAVG = average daily relative humidity; WS = average daily wind speed; SR = total daily solar radiation.
[3]*n* = 46 steers for animal variables; *n* = 42 d for weather variables.
[4]WI%BW was calculated by dividing individual WI (L/d) by daily BW (kg).
[5]Beginning and ending BW are the body weights of all steers on days 1 and 42, respectively.

Table 3.3. Pearson correlation coefficients[1] between average daily linear outcome and predictor variables for 42-d equation development period

Variable[2]	WI%BW	DMI	BW	TAVG	TMIN	TMAX	HAVG	WS	SR
WI	0.962**	-0.093	-0.357*	0.665**	0.346*	0.769**	-0.342*	-0.456**	0.642**
WI%BW		-0.207	-0.594**	0.764**	0.503**	0.811**	-0.234	-0.391*	0.602**
DMI			0.469**	-0.532**	-0.529**	-0.442**	0.181	-0.026	-0.199
BW				-0.669**	-0.684**	-0.542**	-0.152	0.011	-0.218
TAVG					0.863**	0.892**	-0.303	0.046	0.203
TMIN						0.565**	-0.052	0.171	-0.170
TMAX							-0.400**	-0.102	0.504**
HAVG								-0.154	-0.256
WS									-0.588**

[1]Pearson correlation coefficients are significantly greater than 0 at $P < 0.05$ (*) and $P < 0.01$ (**).
[2]WI = water intake, L/d; WI%BW = water intake as a percent of body weight; DMI = dry matter intake, kg/d; BW = daily body weight, kg; TAVG = average daily ambient temperature, °C; TMIN = minimum daily temperature, °C; TMAX = maximum daily temperature, °C; HAVG = average daily relative humidity, %; WS = average daily wind speed, km/h; SR = total daily solar radiation, MJ/m^2.

Table 3.4. Pearson correlation coefficients[1] between average daily outcome and average daily quadratic predictor variables for 42-d equation development period

Variable[2]	**WI%BW**	**DMI^2**	**BW^2**	**TAVG^2**	**TMIN^2**	**TMAX^2**	**HAVG^2**	**WS^2**	**SR^2**
WI	0.962**	-0.062	-0.352*	0.669**	0.117	0.803**	-0.337*	-0.524**	0.631**
WI%BW		-0.175	-0.589**	0.776**	0.232	0.845**	-0.227	-0.453**	0.613**
DMI^2			0.453**	-0.501**	-0.300	-0.381*	0.192	-0.037	-0.184
BW^2				-0.675**	-0.450**	-0.531**	-0.166	0.016	-0.279
TAVG^2					0.374*	0.862**	-0.158	-0.080	0.238
TMIN^2						0.063	0.161	-0.203	0.077
TMAX^2							-0.309*	-0.145	0.488**
HAVG^2								-0.048	-0.214
WS^2									-0.540**

[1]Pearson correlation coefficients are significantly greater than 0 at $P < 0.05$ (*) and $P < 0.01$ (**).
[2]WI = water intake, L/d; WI%BW = water intake as a percent of body weight [(WI, L / BW, kg) * 100]; DMI^2 = dry matter intake squared, kg/d; BW^2 = daily body weight squared, kg; TAVG^2 = average daily ambient temperature squared, °C; TMIN^2 = minimum daily temperature squared, °C; TMAX^2 = maximum daily temperature squared, °C; HAVG^2 = average daily relative humidity squared, %; WS^2 = average daily wind speed squared, km/h; SR^2 = total daily solar radiation squared, MJ/m^2.

Table 3.5. Regression results for water intake (WI) and water intake as a percent of body weight (WI%BW) prediction equations for finishing steers

	Equation [1,2]							
Item [3]	**OVRL**	**DMIO**	**SRO**	**SIMP**	**OVRL**	**DMIO**	**SRO**	**SIMP**
Dependent Variable	WI, L/d	WI, L/d	WI, L/d	WI, L/d	WI, %BW	WI, %BW	WI, %BW	WI, %BW
Intercept	-7.144	23.560	4.565	29.156	0.720	1.960	4.151	4.263
TAVG, °C			0.451					
TMIN, °C	0.272				0.058	0.025	0.034	
BW, kg	0.029		0.032					
DMI, kg/d	1.366				0.250	0.176		
WS, km/h			-0.196					
HAVG, %	-0.051	-0.059		-0.053				
SR, MJ/,m²			0.282					
DMI², kg/d		0.035						
TMAX², °C	0.010	0.014		0.012	0.002	0.003	0.002	0.003
SR², MJ/m²	0.018				0.004		0.002	
WS², km/h	-0.007	-0.012		-0.013	-0.001	-0.002	-0.002	-0.002
TMIN², °C	0.017				0.003	0.004		
R^2	0.933	0.889	0.787	0.835	0.944	0.890	0.861	0.825
RMSE	1.007	1.220	1.694	1.471	0.185	0.255	0.283	0.309
F [4]	57.19	74.27	34.09	63.97	97.58	58.46	57.11	92.05

[1]Overall (OVRL) models included all variables. DMI only (DMIO) models included DMI but excluded SR. SR only (SRO) models included SR but excluded DMI. Simplistic models (SIMP) excluded both SR and DMI.
[2]DMIO WI equation was developed using the forward selection method; whereas, all other equations were developed using the backward selection method. Missing values within a column indicate that those variables were not included in the final equation.
[3]WI = daily water intake; WI%BW = water intake as a percent of BW [(WI, L / BW, kg) * 100]; TAVG = average daily temperature; TMIN = minimum daily temperature; BW = daily body weight; DMI = dry matter intake; WS = average daily wind speed; HAVG = average relative humidity; SR = total daily solar radiation; DMI^2 = daily dry matter intake squared; $TMAX^2$ =

maximum daily temperature squared; SR^2 = total daily solar radiation squared; WS^2 = average daily wind speed squared; $TMIN^2$ = minimum daily temperature squared; R^2 = coefficient of determination; RMSE = root mean square error; F = F-ratio.

[4]All F-ratios were significant at $P < 0.01$.

Table 3.6. Partial R^2 results for variables in water intake (WI) and water intake as a percent of body weight (WI%BW) prediction equations for finishing steers

	Equation[1,2]							
Item[3]	**OVRL**	**DMIO**	**SRO**	**SIMP**	**OVRL**	**DMIO**	**SRO**	**SIMP**
Dependent variable	WI, L/d	WI, L/d	WI, L/d	WI, L/d	WI, %BW	WI, %BW	WI, %BW	WI, %BW
Intercept								
TAVG, °C			0.442					
TMIN, °C	0.020				0.253	0.253	0.253	
BW, kg	0.127		0.021					
DMI, kg/d	0.054				0.005	0.005		
WS, km/h			0.237					
HAVG, %	0.144	0.117		0.117				
SR, MJ/m^2			0.086					
DMI^2, kg/d		0.055						
TMAX^2, °C	0.385	0.537		0.537	0.496	0.496	0.463	0.714
SR^2, MJ/m^2	0.145				0.154		0.022	
WS^2, km/h	0.045	0.181		0.181	0.013	0.086	0.122	0.112
TMIN^2, °C	0.013				0.023	0.051		

[1]Overall (OVRL) models included all variables. DMI only (DMIO) models included DMI but excluded SR. SR only (SRO) models included SR but excluded DMI. Simplistic models (SIMP) excluded both SR and DMI.
[2]Missing values within column indicate that those variables were not included in the final equation.
[3]TAVG = average daily temperature; TMIN = minimum daily temperature; BW = daily body weight; DMI = dry matter intake; WS = average daily wind speed; HAVG = average relative humidity; SR = total daily solar radiation; DMI^2 = daily dry matter intake squared; TMAX^2 = maximum daily temperature squared; SR^2 = total daily solar radiation squared; WS^2 = average daily wind speed squared; TMIN^2 = minimum daily temperature squared.

Table 3.7. Summary statistics[1] for 42 d individual animal and weather variables used to evaluate new finishing water intake equations

Variable[2]	**Mean**	**SD**	**CV%**	**Minimum**	**Maximum**
Animal[3]					
WI, L/d	55.2	17.2	31.2	22.1	132.6
WI%BW	11.1	3.5	31.5	4.3	24.6
DMI, kg/d	11.3	1.6	14.2	5.4	16.6
Beginning BW, kg	450	13	2.9	430	479
Ending BW, kg	554	16	2.9	511	589
Weather[3]					
TAVG, °C	26.60	2.80	10.5	20.62	31.04
TMIN, °C	20.95	3.20	15.3	11.88	25.36
TMAX, °C	32.30	2.95	9.1	22.85	36.94
HAVG, %	66.96	10.61	15.8	51.56	89.28
WS, km/h	11.08	3.09	27.9	5.79	17.54
SR, MJ/m^2	23.35	6.42	27.5	6.33	31.08

[1]Water and feed intakes outside 3 standard deviations of individual animal's daily intakes or the herd's daily intakes were removed from the dataset.
[2]WI = daily water intake; WI%BW = water intake as a percent of body weight [(WI, L / BW, kg) * 100]; DMI = daily dry matter intake; BW = body weight; TAVG = average daily ambient temperature; TMIN = minimum daily temperature; TMAX = maximum daily temperature; HAVG = average daily humidity; WS = average daily wind speed; SR = total daily solar radiation.
[3]*n* = 27 steers for animal variables; *n* = 42 d for weather variables.

Table 3.8. Evaluation results from observed water intake (WI, L/d) or water intake as a percent of BW (WI%BW) regressed on predicted WI for new finishing equations

	Equation[1]							
Item[2]	**OVRL**	**DMIO**	**SRO**	**SIMP**	**OVRL**	**DMIO**	**SRO**	**SIMP**
Dependent Variable	WI, L/d	WI, L/d	WI, L/d	WI, L/d	WI, %BW	WI, %BW	WI, %BW	WI, %BW
Predicted WI	52.9	37.3	37.0	36.5	10.4	9.2	7.9	7.2
R^2	0.60	0.67	0.50	0.64	0.58	0.51	0.57	0.59
Intercept	7.22	-32.83	-32.44	-41.08	1.20	-0.61	-2.39	-6.93
Slope	0.91	2.36	2.37	2.64	0.95	1.28	1.72	2.52
RMSE	5.40	4.87	6.01	5.08	1.18	1.27	1.19	1.16
Mean bias[3]	2.40	18.02	18.32	18.75	0.69	1.96	3.24	3.97
***P*-value**	0.007	<0.0001	<0.0001	<0.0001	0.001	<0.0001	<0.0001	<0.0001
Linear bias[3]	-0.09	1.36	1.37	1.64	-0.05	0.28	0.72	1.52
***P*-value**	<0.0001	0.172	0.326	0.047	<0.0001	0.0008	0.230	0.124

[1]Overall (OVRL) models included all variables. DMI only (DMIO) models included DMI but excluded SR. SR only (SRO) models included SR but excluded DMI. Simplistic models (SIMP) excluded both SR and DMI.
[2]Predicted WI = average daily predicted WI or WI%BW; R^2 = coefficient of determination; RMSE = root mean square error.
[3]Mean and linear biases were calculated by regressing residual predicted WI or WI%BW on mean-centered WI or WI%BW for each equation based on St-Pierre (2003). Mean and linear biases were the intercept and slope terms obtained from those regressions, respectively. *P*-values for mean and linear biases were obtained by performing t-tests to determine if intercept = 0 or slope = 1, respectively.

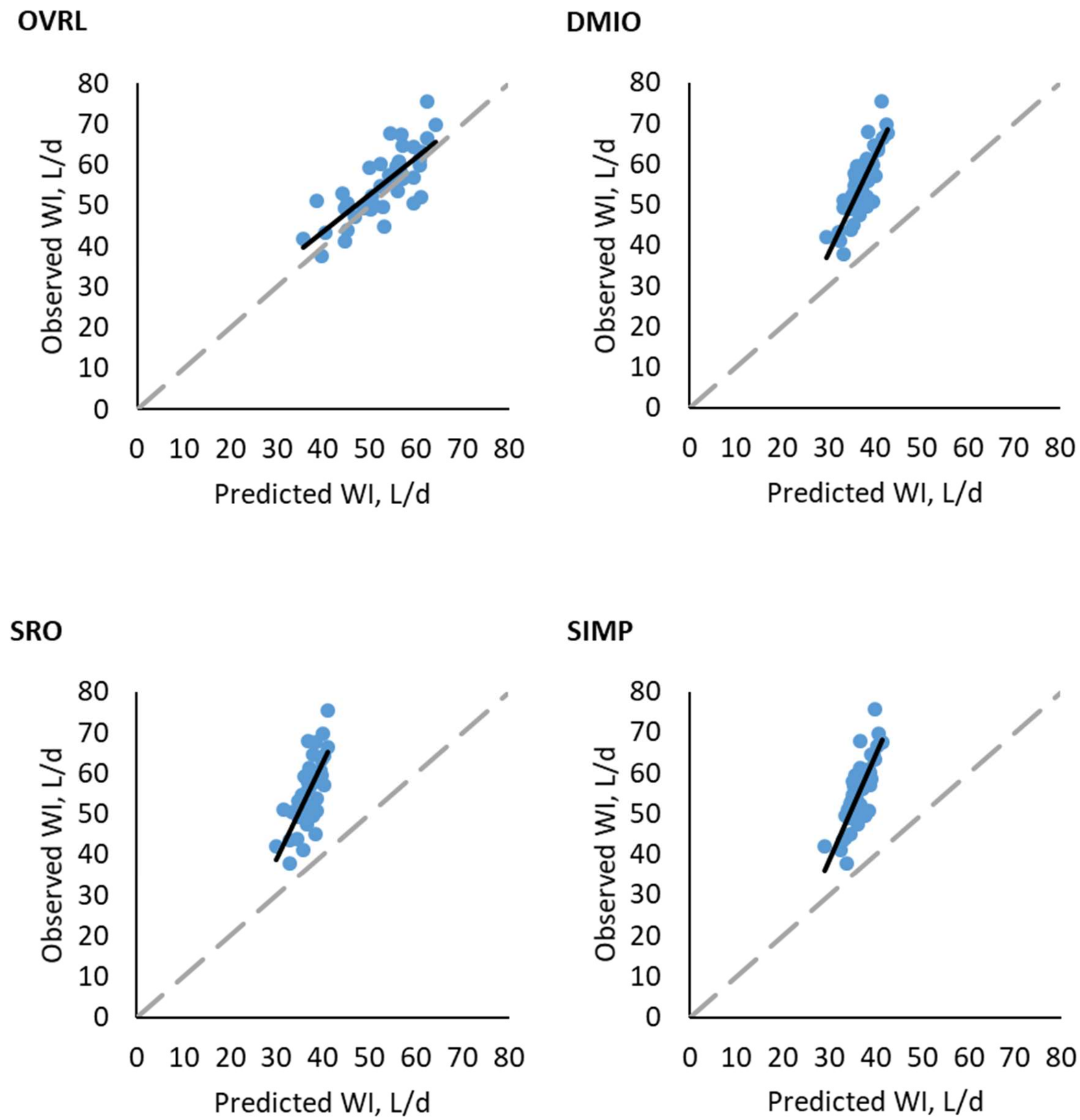

Figure 3.1. Results of observed average daily steer water intake (WI, L/d) regressed on predicted WI during a 42 d evaluation period for new finishing equations. Overall (OVRL) included daily dry matter intake (DMI) and total daily solar radiation (SR) in the model. The DMI Only (DMIO) included DMI, but excluded SR. The SR Only (SRO) included SR, but excluded DMI. Simplistic (SIMP) excluded SR and DMI. The solid line represents the fit of the regression, and the dashed line represents the equality line.

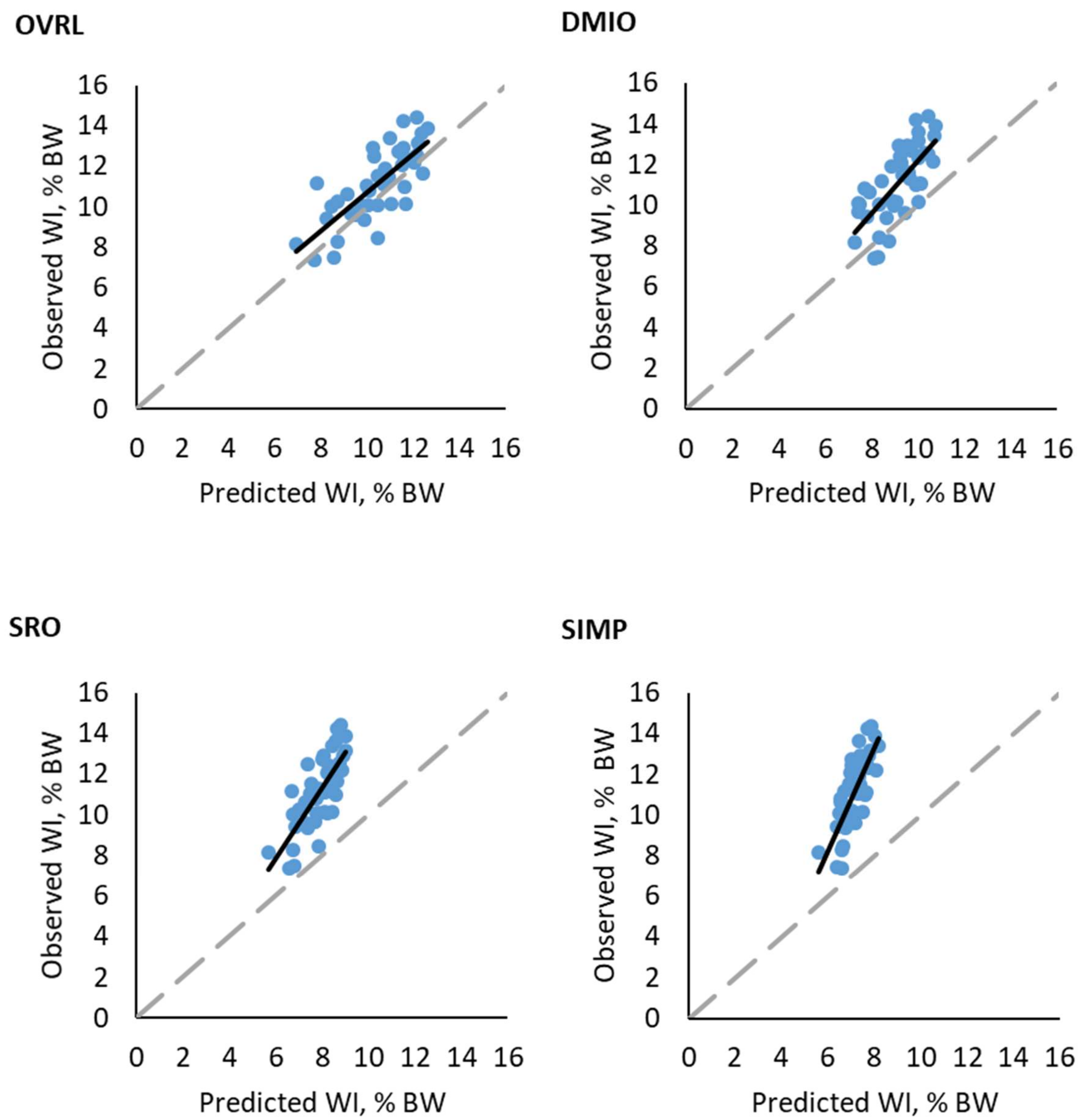

Figure 3.2. Observed average daily steer water intake as a percent of body weight (WI,%BW) regressed on predicted WI, %BW during a 42 d evaluation period for new finishing equations. Overall (OVRL) included daily dry matter intake (DMI) and total daily solar radiation (SR) in the model. The DMI Only (DMIO) included DMI but excluded SR. The SR Only (SRO) included SR but excluded DMI. Simplistic (SIMP) excluded SR and DMI. The solid line represents the fit of the regression, and the dashed line represents the equality line.

VITA

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