ADAPTATION OF A DYNAMIC CROP MODEL FOR ESTIMATING TALL FESCUE FORAGE AVAILABILITY IN THE SOUTHERN GREAT PLAINS

By

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Abstract:
Due to interannual and cross-location variability of forage production, ranchers often encounter difficulties anticipating which management strategies should be used for optimum pastureland management. While models for predicting forage production are available to aid management decisions for some forage crops, there is limited research for a yield model designed specifically for tall fescue (*Festuca arundinacea* Schreb.). Therefore, our objective was to adapt an existing DSSAT-CSM-Perennial forage model for predicting forage biomass of tall fescue in the southern Great Plains. To evaluate model performance, there must first be a high level of data manipulation and cleaning. In this thesis, a cohesive dataset combining biomass, weather, soil, and management data is structured into DSSAT standard file format to be used in future tall fescue crop modeling analysis. Model inputs are obtained from multiple sources, weather data from the Oklahoma Mesonet and the University of Georgia Weather Network and soil data from SSURGO. The model performance was inconsistent in predicting seasonal differences in biomass production. The model is under-predicting harvestable biomass for the agronomic site, Ardmore (AGR), with a mean bias of -376 kg ha^{-1}, and it is over-predicting for the breeder sites with a mean bias of 664 kg ha^{-1}. The model was not able to adequately predict harvestable biomass of tall fescue for either the breeder data [Willmott agreement index (D) of 0.61, a Nash-Sutcliffe model efficiency (ME) of -1.06, root mean squared error (RMSE) of 2408] or the agronomic data (D = 0.63, ME = 0.02, and RMSE = 5124). For the model to provide more accurate predictions of harvestable biomass, further parameterization will be required through calibration of parameters that control above- to below-ground partitioning, response to temperature, and maximum leaf photosynthesis rate. Calibration will require identifying and adapting parameters that negatively affect production which will increase the model's ability to predict forage biomass.

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CHAPTER I

GENERAL INTRODUCTION

1.1 Introduction

Tall fescue (*Festuca arundinacea* Schreb.) is a versatile and important cool-season perennial grass in the United States, covering approximately 15 million ha [37 million acres; Rogers and Locke (2013)] and serving many uses such as reducing runoff, controlling water and wind erosion, and providing pasture and hay for livestock (Ball, Lacefield, and Hoveland, 1991). In the southern Great Plains (SGP), cool-season perennial forages are an essential early season complement to winter annual forage, such as wheat (Reuter and Horn, 2002). Compared with other forages, cool-season perennials offer a longer growing season and exceptional animal performance (Beck et al., 2008).

Tall fescue is an ideal cool-season forage in the SGP because it can withstand the extreme high temperatures and frequent drought of the summer months (Hopkins and Bhamidimarri, 2009). Additionally, the SGP has a bimodal pattern of annual precipitation, peaking in the spring and fall (Malinowski, Kigel, and Pinchak, 2009) when tall fescue is at its peak production and highest quality. These rain events during peak growth allow for tall fescue to be competitive against other forage species (Schuster and De Leon Garcia, 1973). The use of a cool-season perennial grass, such as tall fescue, is a viable option for many ranchers because they do not have to rely on the inopportune timing of autumn precipitation as ranchers do to sow annual crops like wheat (Silva, 2021). Tall fescue can replace and complement those annuals in livestock pastures to improve the economic value of livestock production, decrease soil erosion, and reduce labor (Hopkins, Young, et al., 2011).

The ability to anticipate forage biomass is essential for ranchers who often use flexible stocking densities to maximize productivity. Crop models, such as the Decision Support System for Agrotechnology Transfer Cropping Systems Model [DSSAT-CSM; Jones et al. (2003); Hoogenboom et al. (2019)], have potential to provide important information on tall fescue production by integrating multiple sources of real-world forcing data [e.g. soil, weather, management practices; Pedreira et al. (2011)]. Soil data from the Soil Survey Geographical Database [SSURGO; Soil Survey Staff (2020)] and daily weather inputs from the Oklahoma Mesonet (McPherson et al., 2007; Brock et al., 1995) and University of Georgia Weather Network (Knox et al., 2020) could assist in providing needed high-resolution estimates of tall fescue forage production in the SGP. By feeding these inputs to a dynamic crop model, it theoretically has the ability to predict the growth of a particular crop in a certain environment over time. However, there has been limited research in modeling tall fescue forage production (Kiniry et al., 2018). One constraint of research in this area has been the limited availability of long-term tall fescue biomass data. In order to adequately evaluate a model's qualitative and quantitative accuracy, there must first be a high level of data manipulation and cleaning on a well-characterized dataset.

The remainder of this thesis is organized into three chapters. Chapter 2 focuses on documenting the process by which the tall fescue data were compiled, cleaned and curated. This process resulted in a high-quality integrated biomass, management, soil, and weather dataset in DSSAT standard file format that has the potential to be used for crop simulation modeling of tall fescue. Using this curated dataset, chapter 3 documents the adaptation of an existing DSSAT-CSM-Perennial ryegrass model for estimating harvestable biomass of tall fescue in the SGP. The performance of the adapted model was also evaluated using the curated dataset from chapter 2. In the final chapter of this thesis, we summarize the general findings across chapter 2 and chapter 3 and discuss future directions for model development.

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CHAPTER II

DATA CURATION FOR MODELING TALL FESCUE BIOMASS DYNAMICS WITH DSSAT-CSM

2.1 Introduction

In the southern Great Plains (SGP), cool-season perennial forages serve an essential role as early season complements to winter annual forages, like wheat. To achieve the optimal performance and nutritive value of ones pasture, it would be beneficial to have a model that would predict harvestable biomass. However, there are limited long-term cool-season perennial forage trials available, making it difficult to obtain sufficient input data for a dynamic crop model. In order to adequately evaluate a model's qualitative and quantitative accuracy, there must first be a high level of data manipulation and cleaning to compile a curated dataset. The objective of this chapter is to produce a comprehensive documentation of the dataset for modeling tall fescue harvestable biomass in the southern Great Plains. Therefore, we have created a diverse dataset including biomass data obtained from the Noble Research Institute paired with corresponding weather data from the Oklahoma Mesonet (Brock et al., 1995; McPherson et al., 2007) and the University of Georgia Weather Network (Knox et al., 2020), as well as soil data from the NRCS SSURGO database (Soil Survey Staff, 2020). Through this process, a high quality dataset of biomass, weather, soil, and management data is then structured into a single condensed comprehensive dataset that has been converted into DSSAT standard file format which has the potential to be used for crop simulation modeling of tall fescue.

Table 2.1: Summary data of locations included in the dataset including location, latitude (Lat, decimal degrees), longitude (Long, decimal degrees), elevation (Elev, m), maximum temperature (TMAX) in °C, minimum temperature(TMIN) in °C, and seasonal cumulative rainfall (Rainfall, mm).

Site	**Lat**	**Long**	**Elev**	**TMAX**	**TMIN**	**Rain**
Ardmore	34.19	-97.09	266	23.8	11.7	879
Tifton	31.49	-83.53	118	26.8	15.6	785
Vashti	33.55	-98.04	330	25.4	11.2	421
Woodward	36.42	-99.42	625	23.7	9.8	410

2.1.1 Study Area

The condensed dataset consists of numerous locations and multiple data sources (Figure 2.1). Weather data sources were the Oklahoma Mesonet (Brock et al., 1995; McPherson et al., 2007) and the University of Georgia Weather Network (Knox et al., 2020) and is described in the summary tables by location (Table 2.1) and season (Table 2.2). Table 2.1 suggests that seasonal cumulative rainfall across all sites ranged from 410 mm to 879 mm. Table 2.2 indicates that on a seasonal basis, Woodward, OK had the least amount of cumulative seasonal rainfall and the lowest temperatures, and Tifton, GA had the highest cumulative seasonal rainfall and highest temperatures. The soil data for each site was obtained from the Soil Survey Geographical Database [SSURGO; Soil Survey Staff (2020)]. Management practices vary across sites when evaluating planting date, management, and utilization as seen in Table 2.4. The breeder sites are more similar to one another in management strategies than when compared to the agronomic site.

Table 2.2: Summary of growing season weather across locations for the dataset including location, season (YYYY), maximum temperature (TMAX) in °C, minimum temperature(TMIN) in °C, and seasonal cumulative rainfall (Rainfall, mm).

Site	**Season**	**TMAX**	**TMIN**	**Rain**
Ardmore	2011-2012	25.2	12.7	844
Ardmore	2012-2013	23.8	11.1	719
Ardmore	2013-2014	22.5	10.1	747
Ardmore	2014-2015	21.9	11.0	1639
Ardmore	2015-2016	24.2	12.3	1444
Ardmore	2016-2017	24.7	12.5	701
Ardmore	2017-2018	23.6	11.3	900
Ardmore	2018-2019	22.3	11.4	1576
Ardmore	2019-2020	23.5	11.7	1096
Tifton	2011-2012	27.2	15.5	1043
Tifton	2012-2013	25.4	14.8	1836
Vashti	2011-2012	26.0	12.3	739
Vashti	2012-2013	24.5	10.3	560
Vashti	2013-2014	23.4	9.3	639
Woodward	2011-2012	23.7	10.1	595
Woodward	2012-2013	22.2	8.0	479
Woodward	2013-2014	21.2	7.5	507

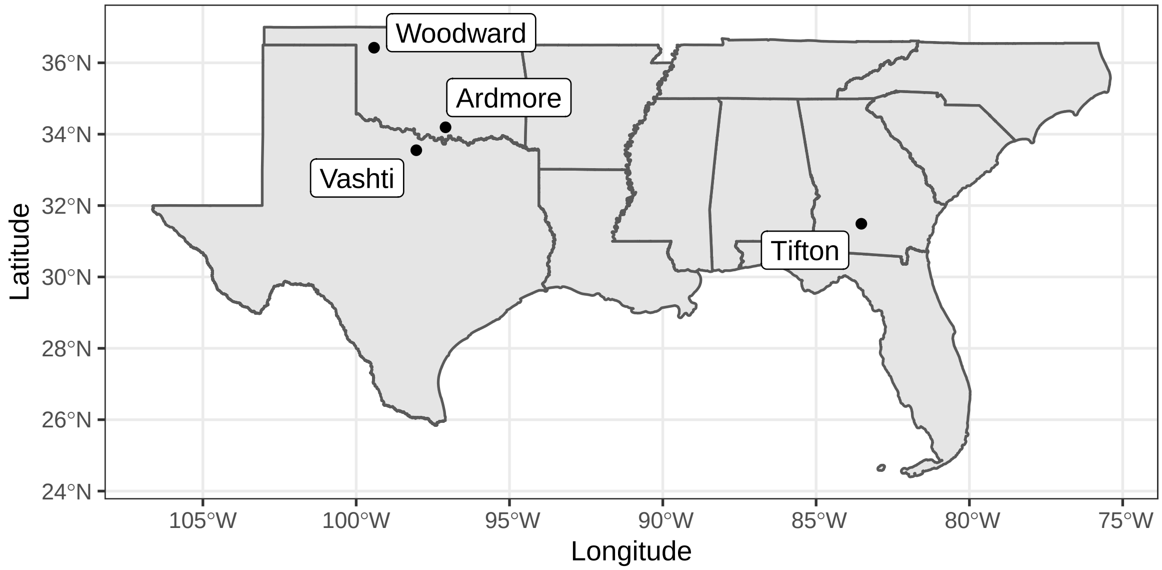

Figure 2.1: Map representing the four locations where biomass data was collected including Ardmore, OK, Tifton, GA, Vashti, TX, and Woodward, OK., as well as the surrounding states.

2.2 Noble Research Institute Tall Fescue Experiments

Tall fescue harvestable biomass samples were collected at five study sites across four locations. The Ardmore location had two studies, an agronomic (AGR) study and a breeder (BRD) trial. The Ardmore, OK (BRD) study from 2012-2014, was managed by individuals outside of the headquarters and classified as a breeder trial for the Noble Research Institute along with the remaining locations, Tifton, GA from 2012-2013, Woodward, OK from 2012-2014, and Vashti, TX from 2012-2014. The agronomic study, Ardmore, OK (AGR), conducted from 2015-2020, had three harvest frequencies and six nitrogen treatments and was directed by researchers at the Noble Research Institute headquarters in Ardmore, OK.

2.2.1 Agronomic Site

Ardmore, OK (AGR)

The Ardmore, OK (AGR) site (34.17° N, 97.17° W; elevation 266 m) was located on a Heiden Clay (fine, montmorillonitic, thermic, Udic Chromusterts) and was planted to the endophyte free tall fescue cultivar, 'Flecha', during the fall of 2013. The site was managed as a cover crop until the establishment of the first field in the fall of 2015. The site was brush-hogged during August of 2014 when the tall fescue stand was dormant to avoid negative impact on growth at the beginning of the experiment. The biomass collected from brush-hogging was recycled to the agronomic site and not removed. The brush hogging technique was chosen because it can to help release new plant growth to potential grazing animals earlier in the growing season, and there would have been minimal feed value if harvested as hay because the harvested material consisted of the prior seasons dead growth. Prior to August 25th, 2015, the dormant standing forage was harvested as hay when the stand was entering its third year after planting, prior to establishing the plots for the experiment.

Harvest frequency varied across AGR with high to low frequency as well as across seasons as shown in Table 2.3. As evidenced in Table 2.3, the AGR site had a complex harvest frequency. The high harvest frequency was the most frequently harvested, being sampled every four weeks in the fall and every two weeks in the spring from 2015 to 2018. Low harvest frequency was the least frequently harvested with one harvest in December and again every six weeks in the spring from March until the end of the growing season for 2015 to 2018 . This same trend holds true for 2018 to 2020 where harvest frequency decreases from high to low respectively. The experiment was designed with multiple harvest frequencies to mimic different management practices such as rotational grazing or cutting hay.

The agronomic site was planted in the fall of 2013 and was fertilized with P and K to soil sufficiency levels based on soil test results (Melich III for P) using 20.4 kg P ha^{-1} (45 lb P acre^{-1}) in P2O5 and 108.9 kg K ha^{-1} (240 lb K acre^{-1}) in K20. The plot was pre-planted with 22.68 kg N ha^{-1} (50 lb N acre^{-1}) in the 2013 establishment year and 22.68 kg N ha^{-1} (50 lb N acre^{-1}) in the fall of 2014. Supplemental amounts of 0-46-0 and 0-0-60 (N-P-K) were applied based on the soil test results from the summer of 2014. No additional N above the 22.68 kg N ha^{-1} maintenance application was supplied and all fertilizer rates were applied per acre.

The study started with five levels of nitrogen in the form of ammonium nitrate (34-0-0, NPK) at the start of the experiment: 0, 56, 112, 168, and 224 kg N ha^{-1} each applied as a split rate (half of the N application for that respective location applied at separate times) in early September and again in late January to early February to capture early season green-up and maximize growth potential. An additional N level at 28 kg N ha^{-1} was also added starting in the fall of 2016 using the same management. These six levels of nitrogen, 0, 28, 56, 112, 168, and 224 kg N ha^{-1} with a split application were maintained until the fall of 2018. From the fall of 2018 through 2020, full rates of N were applied in ammonium nitrate at three different levels: 0, 28, and 112 kg N ha^{-1} applied once in September. Management intentions were to stimulate maximum forage growth over time to create varying biomass production for the forage model.

The experiments at the agronomic site in Ardmore (AGR) had an intricate organization. Figure 2.2 and Figure 2.3 illustrate the layout of the experiments across seasons. The experiments were conducted in two main phases: 2015 to 2018 and 2018 to 2020. The first phase was initiated in the fall of 2015 with twenty 7.6 m by 4.6 m (25ft x 15ft) plots arranged into five rows and four columns (Fig. 2.3). Each column was treated as a block, within which, five N levels (0, 56, 112, 168, and 224 kg N ha^{-1}) were randomly assigned. Within each block, 7.6 m by 1.5 m (25ft x 5ft) subplots were created by assigning the three different harvest frequencies in decreasing frequency from high to low in the West to East direction (Fig. 2.3). For the latter two seasons of phase one (2016-2018), a set of four 7.6 m by 4.6 m plots were added directly adjacent to the North of the existing set of plots (Fig. 2.2). This addition resulted in a total of 24 plots with six N levels (0, 28, 56, 112, 168, and 224 kg N ha^{-1}) for the seasons 2016-2018.

In the 2018-2019 season, the second phase of experiments was established in an area adjacent to but separate from the existing plots from phase one (Fig. 2.2). The trial established in 2018-2019 had sixteen plots with four rows and four columns. In this second phase, two N levels (28 and 112 kg ha^{-1}) were combined with three harvest frequencies to create six unique treatment levels. These unique treatment combinations were then randomly assigned to the sixteen plots (Fig. 2.3). In 2019-2020, the trial was moved back to the original area from the 2015-2016 season (Figure 2.2) and the six treatment combinations were randomly assigned to 16 of the original 20 plots. Four of the original 20 plots (represented by the white boxes in Figure 2.3) were excluded from the study due to issues with pasture persistence and weedy encroachment.

At harvest, each plot was mowed to 2.5-cm stubble height and vegetation was removed without grazing. To measure the average canopy height (cm) the harvestable section was randomly measured with a meter stick and recorded as “CanopyAvgStick”. Mowing was used to promote the new plant growth and to mimic a grazing scenario. No exclosures were present at the site. All forage yield data was recorded on a dry matter (DM) basis. Forage yield was measured as oven-dried clipped forage mass in kg ha^{-1}. Duplication exists as there were two samples taken per (sub)plot and labeled with the same “PlotID”.

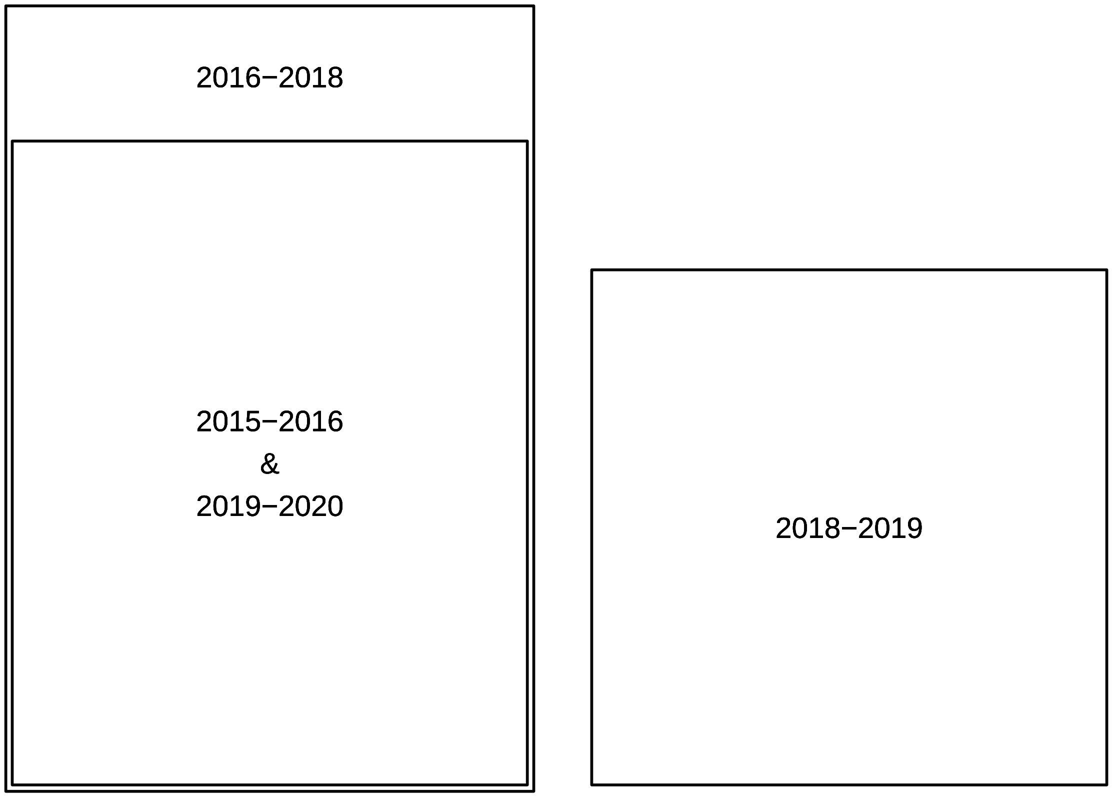

Figure 2.2: Area diagram of the agronomic plots at Ardmore, OK (AGR) and which season each field was host of the study.

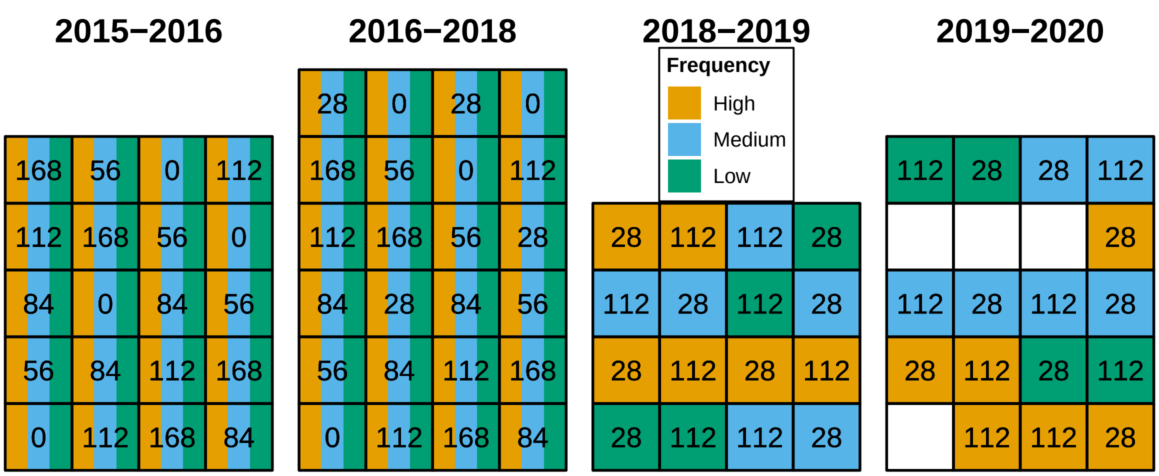

Figure 2.3: Plot layout of each field organized by season, harvest frequency, and nitrogen level.

Table 2.3: Harvest frequency table explained by season for each location, Ardmore, OK, Tifton, GA, Vashti, TX, and Woodward, OK.

Experiment	Season	Frequency	Fall	Spring
Ardmore (AGR)	2015-2018	High	Every 4 weeks October-December	Every 2 weeks March-end of season
		Medium	Every 4 weeks November- December	Every 4 weeks March-end of season
		Low	Once in December	Every 6 weeks March-end of season
Ardmore (AGR)	2018-2020	High	Every 4 weeks October-December	Every 2 weeks March-end of season
		Medium	Every 8 weeks November-December	Every 4 weeks March-end of season
		Low		Once end of season
Ardmore (BRD)	2012-2014			Once end of season
Tifton	2012-2013			Once end of season
Vashti	2012-2014			Once end of season
Woodward	2012-2014			Once end of season

2.2.2 Breeder Sites

Ardmore, OK (BRD)

The Ardmore, OK (BRD) study (34.11° N, 97.05° W; elevation 240 m) was conducted on a Windthorst fine sandy loam (fine, mixed, active, thermic Udic Paleustalf). There were five cultivars of tall fescue including, Flecha-Nil, Chisholm, Texoma MaxQII, Kentucky31, and Prosper. This site was established on October 4^{th}, 2011 and was harvested once in 2012 on March 13^{th}, three times in the spring of 2013 on March 14^{th}, May 20^{th}, and June 24^{th}, and once in 2014 on May 1^{st}.

Tifton, GA

The Tifton, GA breeder site (31.49° N, 83.53° W; elevation 118 m; Tifton loamy sand [fine-loamy, kaolinitic, thermic Plintic Kandiudult]) was composed of a variety of summer-dormant cultivars, Bardiso, Chisholm, Flecha, Ky. 31 E+, MALMA, Prosper, Royal Q100, Taita, and Texoma MaxQII. Tifton was seeded into a bermudagrass sod on November 11^{th}, 2003 and managed as a cover crop until the trial began on November 2^{nd}, 2011. Tifton was the only two season experiment having only harvested biomass yield on April 2^{nd}, 2012, and April 30^{th}, 2013.

Woodward, OK

The Woodward, OK breeder site (36.25° N, 99.24° W; elevation 605 m; Carey silt loam [fine- silty, mixed, super active, thermic Typic Argiustoll]) was established on September 26^{th}, 2011 to evaluate harvestable biomass only under dry-land conditions. The study focused on the summer-dormant varieties, Flecha-Nil, Kentucky31, NFTF-1700-Nil, Prosper, and Texoma MaxQII. Harvests occurred once a season from 2012 to 2014: May 1^{st}, 2012, May 20^{th}, 2013, and May 23^{rd}, 2014.

Vashti, TX

The Vashti, TX site (33.55 N, 98.04° W; elevation 330 m; Anocon loam [fine, mixed, active, thermic Ultic Paleustalfs]) was established on October 21st, 2011. This site was harvested once in 2012 on April 19th, and twice in 2013 on April 4th and July 1st, and again on June 2nd, 2014.

Breeder Site Management

The breeder sites, Ardmore, OK (BRD), Tifton, GA, Vashti, TX, and Woodward, OK had similar management practices. For the breeder sites, the experiments were set up in 2011 using a randomized complete block design (Trammell et al., 2018). With a small plot cone-drill (Hege Equipment), 17 kg ha^{-1} of seed were put into 7 rows of clean, tilled seedbeds. The Ardmore (BRD), Tifton, and Vashti locations were set up in a 1.5 m by 6.1 m (5ft x 20ft) plot with four replications. Unlike the other breeder sites, Woodward had five replications in a 1.5 by 7.6 m (5 by 25 ft) plot (Trammell et al., 2018). For each of the breeder sites, there was a single application of ammonium nitrate (N–P–K, 34–0–0) at the rate of 46 kg N ha^{-1} at the time of sowing or early fall of each season. An application of 2,4-D (2, 4 D-dichlorophenoxyacetic acid) low volatile ester was applied to the Ardmore (BRD) and Vashti sites at the rate of 1.12 kg a.i. ha^{-1} to control broad leaf weeds in the spring following establishment. Samples were collected using a sickle bar plot harvester at a height of approximately 7-cm (Trammell et al., 2018).

2.3 Data Aquisition and Quality Control

Data for each location was collected and captured using manual data entry into a spreadsheet format. Names were generated for each column to correspond with standard DSSAT input variables and were made uniform across all locations.

R version 4.1.2 (R Core Team, 2021) was used to analyze and clean all data. The

Table 2.4: Summary data of the management information across each location in the dataset including a four-digit location code (LLLL), residual stubble mass kg ha^{-1}, and planting date (MM-DD-YYYY)

Site	Residual	Planting Date
ARD2	760	09-15-2013
ARDB	1800	09-26-2011
TIFT	1800	11-02-2011
VASH	1800	09-26-2011
WOOD	1800	09-26-2011

R package `tidyverse` (Wickham et al., 2019) was used to perform data cleaning and curation. As each variable of the database was brought in, a screening process was performed to account for all duplication or spelling errors; these inconsistencies were standardized and corrected to produce a harmonized dataset. Numerical variable units were converted to standard International System of Units (SI). The text and numerical modifications were performed using R code, to avoid introducing manual typographical errors and to ensure reproducibility of the workflow.

The coordinates for Ardmore, Woodward, and Vashti were taken from Trammell et al. (2018). Coordinates for the Tifton site were estimated using Google Maps (https://www.google.com/maps). These coordinates were then used to extract the SSURGO soil profile data and to match experimental sites with nearby weather stations for extracting daily weather.

2.3.1 Weather Data

Weather data near each location were obtained from the Oklahoma Mesonet (Brock et al., 1995; McPherson et al., 2007) and the University of Georgia Weather Network (Knox et al., 2020). The Oklahoma Mesonet is an automated network of 122 meteorological stations across the state that have been collecting data since 1994 (Brock et al., 1995; McPherson et al., 2007). Weather data are collected in 5-minute intervals continuously by each station and are transmitted to a central facility to be quality controlled, distributed, and archived (Shafer et al., 2000). Mesonet time series (MTS) files with 5-min data were downloaded from the Oklahoma Mesonet website, imported into R and summarized to produce daily values for near-surface cumulative solar radiation (MJ m^{-2} d^{-1}), rainfall (mm d^{-1}), average relative humidity (percent), 2 meter wind speed (km d^{-1}), as well as maximum and minimum temperature (°C). Daily weather data was obtained for each site, Ardmore (January 1st, 2011 to November 1st, 2020), Vashti (January 1st, 2011 to December 31st, 2014), Woodward (January 1st, 2011 to November 1st, 2014), and Tifton (January 1st, 2011 to December 31st, 2013). For the Oklahoma and Texas sites, weather data were obtained from the Oklahoma Mesonet (Brock et al., 1995; McPherson et al., 2007) at the following stations: Ardmore (ARD2), Woodward (WOOD), and Waurika (WAUR). The WAUR station was used for the Vashti, TX site even though it was located approximately 70 km (44 mi) from the site, because there was no other resource that provided reliable and well documented weather data needed for the dynamic crop model. The Georgia weather data was received from the University of Georgia Weather Network at the Tifton (TIFT) site (Knox et al., 2020).

Weather station metadata for latitude (LAT), longitude (LONG), and elevation (ELEV) were pulled for the Oklahoma and Texas sites using the `okmesonet` package in R (Allred, Hovick, and Fuhlendorf, 2014). The reference height for air temperature measurement (REFHT) was set to 1.5 m and the reference height for wind speed (WNDHT) was set to 2 m. Atmospheric CO_2 concentration (CO2) was set to a null value of NA. Weather station metadata for Tifton were derived in a similar way from multiple sources (Knox et al., 2020), except that WNDHT was set to 3 meters following Georgia Weather Network documentation (Knox et al., 2020).

To generate a DSSAT format weather files, long-term average temperature (TAV), as well as the amplitude (AMP) of the long-term average annual temperature, were calculated. The long-term average temperature was computed as the average of TMAX and TMIN and then averaged over all dates of measurement. The temperature amplitude was calculated first by summarizing the monthly average temperature of the observation period. The lowest monthly average temperature was subtracted from the highest monthly average temperature and divided by 2. Those values were combined with other location-specific information including a location code (INSI), LAT, LONG, ELEV, TAVG, AMP, REFHT, WNDHT, and CO2 that is required for the DSSAT-formatted header information. Occasional gaps in daily weather records were filled using linear interpolation across days for all variables except rainfall. Missing rainfall data were assumed to be zero. The daily weather data and weather station metadata for each site were combined to a DSSAT standard format weather file, as shown in Table 2.5, and were written using the function `write_wth` from the DSSAT package (Alderman, 2020; Alderman, 2021).

2.3.2 Soil Data

Soil names were provided in the tall fescue datasets corresponding with each location. The soil names from each location were used to pull the soil profiles from the Soil Survey Geographical Database (SSURGO) (Soil Survey Staff, 2020) for each location through a custom utility function written for this purpose, `pull_profile_by_name()`. Initially, the function queries the SSURGO database using a function, `SDA_query()` from the package `soilDB`, Version 2.5 (Beaudette, Skovlin, and Roecker, 2020) to search the soil name provided. If multiple entries are returned, the function then filters the provided map unit keys by constructing a query based on the location coordinates and selects the map unit key of the nearest feature using the function `st_nearest_feature()` of the `sf` package (Pebesma, 2018). The component- and horizon-specific soil property data were then pulled from the identified map unit key. These data were combined and used to make a DSSAT soil profile object.

The multiple methods by which soil input data were derived included using SSURGO data directly and deriving approximate equivalent values. Soil albedo (SALB) values were taken directly from SSURGO (albedodry_r). Soil organic carbon (SLOC) was set to the SSURGO value for soil organic matter (om_r) divided by a standard 1.724. Soil drainage (SLDR) was estimated based on the SSURGO value for drainagecl_r, from "Excessively drained" soils being assigned a value of 0.85 to "Very poorly drained" soils being assigned a value of 0.01. The Soil Conservation Service runoff curve number for antecedent soil moisture condition II (SLRO) was set based on the SSURGO values for hydrologic soil group (hydgrp) and slope (slope_r). The depth to base of layer (SLB) was pulled from the corresponding SSURGO variable (hzdepb_r). The soil coarse fraction (SLCF) was taken from the SSURGO variable fragvol_r. When a value for fragvol_r was missing and the horizon name indicated the presence of bedrock, SLCF was assumed to be 99. Otherwise, SLCF was assumed to be 0. To calculate the soil root growth factor (SRGF), the SLCF was divided by 100 and subtracted from 1.

The SSURGO data for volumetric water content (VWC) at -0.33 bar (wthirdbar_r) and -15 bar (wfifteenbar_r), bulk density (dbtenthbar_r, dbthirdbar_r, or dbovendry_r), percent silt (silttotal_r), and percent clay (claytotal_r) were extracted for each soil profile to generate estimates of the saturated conductivity. Saturated hydraulic conductivity (SSKS) was converted from cm d^{-1} to cm h^{-1} to fit the units required by the DSSAT variable definition. The soil lower limit (SLLL) was assumed to be VWC at -15 bar (wfifteenbar_r, i.e. soil water at -1500 kPa or permanent wilting point for the crop). Soil drained upper limit (SDUL) was assumed to be equal to VWC at -0.33 bar (wthirdbar_r). Saturated value (SSAT) was set at 95 percent of the pore space. Pore space was calculated as $1 - \frac{SBDM}{2.65}$, where SBDM is bulk density in g cm^{-3} and particle density was assumed to be 2.65 g cm^{-3}. Where available, SBDM was set to dbtenthbar_r. If values for dbtenthbar_r were missing, values from dbthirdbar_r were used. If both of these were missing values, dbovendry_r was used.

The values for soil mineralization factor (SLNF) and soil photosynthesis factor (SLPF) were both assumed to be 1 and the soil evaporation limit (SLU1) was set to 6 mm. Parameters indicating method of extraction (SMHB, SMPX, and SMKE) were set to nominal values of IB001. All other soil input data values were set as missing. A full description of soil variables and units is provided in Table 2.6. Soil input data were written to the DSSAT standard soil file format using the `write_sol()` function from the DSSAT version 0.0.4 R package (Alderman, 2020; Alderman, 2021).

2.4 Data File Description

This chapter describes the process of compiling one comprehensive dataset in the form of DSSAT standard format for observed biomass (FileT), management data (FileX), weather data (.WTH), and soil data (.SOL) from a range of environments that will permit further model development, parameterization and evaluation.

File names are specified as an eight-digit code that is unique to each location, year and management combination followed by a three-digit file extension of either U2X (FileX) or U2T (FileT). The FileX and FileT share the same eight-digit code containing the corresponding definition of management (FileX) and observed data (FileT). The FileT contains columns for treatment number (TRNO), date of collection (DATE), and harvestable biomass kg ha^{-1} (FHWAH). The FHWAH column contains data of harvested biomass which excludes a 7-cm residual stubble for breeder sites and a 2.5-cm residual stubble for the agronomic site. Within the FileX, the treatment number column, within the TREATMENTS section, corresponds to the TRNO column of the FileT; the ID_SOIL column, in the FIELDS section, links the soil type in the soil data file, and the WSTA column, in the FIELDS section, links to the corresponding weather file. The PDATE and HDATE columns provide the planting and harvest dates, respectively, for the specific location, year and management combination.

The unique values of the eight-digit code were generated according to the following pattern LLLLYYMM.XXX, where LLLL was the four-digit location code as shown in Table 2.5, YY was the two-digit year at the end of the harvest season, and MM was a two-digit management code), and XXX was a three-digit file extension indicating the DSSAT standard file type. Within the two-digit management code, the first digit indicates waterstress (0 for no water applied, I for irrigated), second digit is harvest frequency (A for most frequently harvested, B for medium harvest frequency, C for the least frequently harvested, 0 for breeder sites with a standard harvest frequency). The DSSAT standard file format code consists of a two-digit crop identification code (U2 for Unidentified crop; DSSAT does not currently have a code for tall fescue) and a single digit file type code (X for FileX and T for FileT).

Weather data were stored in DSSAT-formatted weather files where each file corresponds to a specific location, year, and management combination. Weather files were named using the following pattern LLLLYYMM.WTH, where LLLL was the four-digit location code, YY was the two-digit year at the beginning of start up for that respective location, and MM (a two-digit management code denoting how many years of weather data were collected), and WTH is the three-digit file extension denoting a DSSAT-formatted weather file. Weather files can be read into R using the `write_wth()` function of the `DSSAT` R package (Alderman, 2020; Alderman, 2021). Variable descriptions for weather files are found in Table 2.5. Similarly, soil entries are stored in a DSSAT-formatted soil file, using the extension SOL, which stores whole-profile and layer-specific soil variables described in Table 2.6. Soils for each location are referenced by the ID_SOIL. The soil data file can be read into R using the `read_sol()` function from the `DSSAT` R package (Alderman, 2020; Alderman, 2021).

Table 2.5: Name, definitions and units for weather variables reported in a standard DSSAT formatted weather file (.WTH).

Name	Description	Units
AMP	Temperature amplitude	°C
CO2	Carbon dioxide concentration	ppm
DATE	Date of observation	YYJJJ*
ELEV	Elevation	m
INSI	Institute and site code	code
LAT	Latitude	decimal degrees north
LONG	Longitude	decimal degrees east
RAIN	Daily rainfall	mm d^{-1}
REFHT	Reference height for weather measurements	m
RHUM	Relative humidity	percent
SRAD	Daily solar radiation	MJ m^{-2} d^{-1}
TAV	Temperature average for whole year	°C
TMAX	Daily temperature maximum	°C
TMIN	Daily temperature minimum	°C
WIND	Daily wind speed	km d^{-1}
WNDHT	Reference height for windspeed measurements	m

* YYJJJ, two-digit year followed by three-digit Julian day of year.

Table 2.6: Name, definitions and units for soil variables reported in a standard DSSAT formatted soil file (.SOL).

Name	**Description**	**Units**
COUNTRY	Country of soil profile location	–
LAT	Latitude	decimal degrees north
LONG	Longitude	decimal degrees east
SADC	Soil adhesion coefficient	0 to 1 scale
SALB	Albedo	fraction
SBDM	Bulk density	g cm^{-3}
SCEC	Cation exchange capacity	cmol kg^{-1}
SCOM	Color	Munsell hue
SCS FAMILY	Soil Conservation Service soil family	–
SDUL	Upper limit	cm^3 cm^{-3}
SITE	Site name	Site name
SLB	Depth	cm
SLCF	Coarse fraction (>2 mm)	percent
SLCL	Clay (<0.002 mm)	percent
SLDR	Drainage rate	fraction day^{-1}
SLHB	pH in buffer	pH in buffer
SLHW	pH in water	pH in water
SLLL	Lower limit	cm^3 cm^{-3}
SLMH	Master horizon	Master horizon
SLNF	Mineralization factor	0 to 1 scale
SLNI	Total nitrogen	percent
SLOC	Organic carbon	percent

Table 2.6: Name, definitions and units for soil variables reported in a standard DSSAT formatted soil file (.SOL). *(continued)*

Name	**Description**	**Units**
SLPF	Photosynthesis factor	0 to 1 scale
SLRO	Soil Conservation Service runoff curve number	number
SLSI	Silt (0.05 to 0.002 mm)	percent
SLU1	Evaporation limit	mm
SMHB	pH in buffer determination method	code
SMKE	Potassium determination method	code
SMPX	Phosphorus determination code	code
SRGF	Root growth factor	0 to 1 scale
SSAT	Upper limit	cm^3 cm^{-3}
SSKS	Saturated hydraulic conductivity	cm h^{-1}

2.5 Summary

There has been limited research in the area of tall fescue modeling. Because there are few long-term tall fescue trials that provide adequate characterization needed for modeling, we developed a comprehensive dataset that can be used for future modeling of tall fescue. For this project, biomass data was provided by the Noble Research Institute and included five experiments across four different locations, Ardmore, OK, Tifton, GA, Vashti, TX, and Woodward, OK. This chapter provides an exhaustive description of each site, and the management and sampling practices conducted at each. The chapter also serves to explain the process by which weather and soil data were obtained and manipulated. Soil names from each location were used to pull the soil data from the NRCS-SSURGO (Soil Survey Staff, 2020). Daily weather data and weather station metadata were received from the Oklahoma Mesonet and the University of Georgia Weather Network. These inputs were combined for four locations and multiple growing seasons to compile a curated dataset. The dataset documented here provides DSSAT standard format for observed biomass (FileT), management data (FileX), weather data (.WTH), and soil data (.SOL) from a range of environments that will permit further model development, parameterization and evaluation.

2.6 References

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CHAPTER III

ADAPTATION OF A DYNAMIC CROP MODEL FOR ESTIMATING HARVESTABLE BIOMASS OF TALL FESCUE IN THE SOUTHERN GREAT PLAINS

3.1 Abstract

Due to inter-annual and cross-location variability of forage, ranchers often encounter difficulties anticipating which management strategies should be used for optimum pastureland management. While models for predicting harvestable biomass are available to aid management decisions for some forage crops, there is limited research on yield models designed specifically for tall fescue. Therefore, our objective was to develop a biomass production model for tall fescue by adapting an existing DSSAT-CSM-Perennial forage model for ryegrass. Our model was developed using measured biomass data from four locations: Ardmore, OK, Woodward, OK, Vashti, TX, and Tifton, GA, weather data from the Oklahoma Mesonet and University of Georgia Weather Network, and soil data from SSURGO. To better fit the growth pattern of tall fescue, the primary adaptations of the existing perennial forage model included changing parameters that control dormancy, position of storage tissue, and leaf-level photosynthetic rate. Model performance was inconsistent in predicting seasonal differences in biomass production. The model under-predicted harvestable biomass for the agronomic site, Ardmore (AGR), with a mean bias of -376 kg ha^{-1}, and over-predicted for the breeder sites with a mean bias of 664 kg ha^{-1}. The model was not able to adequately predict harvestable biomass of tall fescue for either the breeder data (Willmott agreement index (D) of 0.61, a Nash-Sutcliffe model efficiency (ME)

of -1.06, root mean squared error (RMSE) of 2408.) or the agronomic data (D = 0.63, ME = 0.02, and RMSE = 5124). For the model to provide more accurate predictions of harvestable biomass, further adaptations of more parameters are needed, such as those which control above- to below-ground partitioning, response to temperature, and maximum leaf photosynthesis rate. Calibration will require identifying and adapting parameters that negatively affect biomass which will increase the model's ability to predict harvestable biomass and provide managers with a way to decrease variability.

3.2 Introduction

Tall fescue (*Festuca arundinacea* Schreb.) is a versatile and important cool-season perennial forage in the United States, covering approximately 15 million ha [37 million acres; Rogers and Locke (2013)] and serving many uses such as reducing runoff, controlling erosion, and providing pasture and hay for livestock (Ball, Lacefield, and Hoveland, 1991). In the southern Great Plains (SGP), cool-season perennial forages are an essential early season complement to winter annual forage, such as wheat (Reuter and Horn, 2002). Compared with other forages, cool-season perennials offer a decreased risk of stand establishment compared to annual forage crops, a longer growing season, and exceptional animal performance (Beck et al., 2008).

Tall fescue is an ideal cool-season forage in the SGP because it can withstand the extreme high temperatures and frequent drought of the summer months (Hopkins and Bhamidimarri, 2009). Additionally, the SGP has a bimodal pattern of annual precipitation, peaking in the spring and fall (Malinowski, Kigel, and Pinchak, 2009) when tall fescue is at its highest quality. The use of a cool-season perennial grass, such as tall fescue, is a viable option for many ranchers because they do not have to rely as heavily on the inopportune timing of autumn precipitation for stand establishment as ranchers do with the annual crop wheat (Silva, 2021). Tall fescue can replace and complement those annuals in livestock pastures to improve the economic value of livestock production, decrease soil erosion, and reduce labor (Hopkins, Young, et al., 2011).

The ability to anticipate forage biomass is essential for ranchers who often use flexible stocking densities to maximize productivity. It is difficult for ranchers to anticipate proper management strategies to optimally manage pastureland due to inter-annual and cross-location variability of forage. Existing forage models have proven to be a useful tool for understanding relationships between soil, weather, and plant phenology, especially when studying among systems over time (Pedreira et al., 2011). One such tool is the Decision Support System for Agrotechnology Transfer Cropping Systems Model (DSSAT-CSM) perennial forage model (James W Jones et al., 2003; Hoogenboom, Porter, Boote, et al., 2019; Hoogenboom, Porter, Shelia, et al., 2022). This system has routines for crops including soybean (*Glycine max* L.), peanut (*Arachis hypogea* L.), dry bean (*Phaseolus vulgaris* L.), faba bean (*Vicia faba* L.), tomato (*Lycopersicon esculentum* Mill.), Pigeonpea (*Cajanus cajan* (L.) Millsp.), guineagrass (*Panicum maximum* Jacq. cv. 'Tanzânia') and the pasture grasses, marandu palisade grass (*Brachiaria brizantha*) and bermudagrass (*Cynodon dactylon*) (Scholberg et al., 1997; Boote, J W Jones, et al., 1998; Boote, James W Jones, et al., 1998; Boote, Mínguez, and Sau, 2002; Phillip D Alderman et al., 2015; Lara et al., 2012; Pequeno et al., 2018). An important feature of dynamic crop models is that they show carry-over effect in the simulated data. This ensures that management practices of the past affect future predictions.

However, there is limited research on crop models for predicting tall fescue harvestable biomass (Kiniry et al., 2018). This suggests that upon calibration of this model, it will help ranchers to predict biomass yield of their tall fescue pastures and aid in calculating stocking rate, carrying capacity, and nutritive value of their land.

Therefore, the objective of this study was to adapt an existing DSSAT-CSM-Perennial ryegrass model for predicting harvestable biomass of tall fescue in the SGP.

We hypothesized that the adapted DSSAT-CSM-Perennial Forage Model can reliably predict (D $\geq$ 0.9, ME $\geq$ 0.65, and nRMSE <0.25) harvestable biomass of tall fescue for the SGP.

3.3 Methods

3.3.1 Study Area

The climate of the SGP is well suited for summer-dormant varieties of perennial cool-season grasses including tall fescue because of its bimodal growth pattern and its ability to withstand drought. The SGP climate (humid subtropical to cold semi-arid) is indicative of summers with severe droughts and extreme temperatures. These climatic factors often cause photo-period, heat, and water stresses (Hopkins and Bhamidimarri, 2009).

The data used for this study come from five field trial sites across four locations (Table 3.1). Four of the five trial sites were breeder-run cultivar performance trials conducted near the Noble Research Institute headquarters in Ardmore, OK from 2012-2014, in Tifton, GA from 2012-2013, in Woodward, OK from 2012-2014, and in Vashti, TX from 2012-2014. A separate set of agronomic trials was also conducted at NRI headquarters in Ardmore, OK from 2015-2020. [The breeder trial at Ardmore is denoted as Ardmore (BRD) and the agronomic trial is denoted as Ardmore (AGR).] The agronomic trials tested a range of harvest frequencies and nitrogen application levels. For this study, data were limited to the only variety common to all trials, Flecha or Flecha-Nil, an endophyte free variety of tall fescue. A detailed description of sites and management are provided in chapter 2 and a summary of the management and data collected are provided in the following section.

3.3.2 Biomass Data

Agronomic Site at Ardmore

The Ardmore (AGR) site (34.17° N, 97.17° W; elevation 266 m) was located on a Heiden Clay (fine, montmorillonitic, thermic, Udic Chromusterts) and was planted to the endophyte free tall fescue cultivar, Flecha, during the fall of 2013. The site was managed as a cover crop until the first harvest in 2015. Harvest frequency varied across AGR (high, medium, low) as well as across seasons (Table 3.1).

Ardmore, OK (AGR) had a complex harvest frequency; the high harvest frequency was the most frequently harvested, being sampled every four weeks in the fall and every two weeks in the spring from 2015 to 2018. The low harvest frequency was the least frequently harvested from 2015 to 2018 with one harvest in December and every six weeks in the spring from March until the end of the growing season (Table 3.1). A similar trend holds true for 2018 to 2020; harvest frequency decreases from high to low. The experiment was designed with multiple harvest frequencies to mimic different management practices such rotational grazing or cutting hay. The plot was mowed to 2.5-cm stubble height at each harvest date and vegetation was removed without grazing. The plot was mowed in August of 2014 when the fescue was the most dormant, and residue was recycled to that site and not removed. The dormant standing forage was harvested before August 25th, 2015, prior to establishing the plots as the stand was entering its third season after planting. The study was initiated in the fall of 2015 with five levels of N applications: 0, 56, 112, 168, and 224 kg N ha^{-1} as ammonium nitrate (34-0-0) each applied in a split rate application, half in the fall and half in the spring. An additional treatment of 28 kg N ha^{-1} was added to the experimental design in the fall of 2016 and was maintained until the fall of 2018. From 2018-2020, two N levels (28 and 112 kg N ha^{-1}) were applied as a single application of ammonium nitrate in the fall of each season. Management practices

Table 3.1: Harvest frequency table explained by season for each location, Ardmore, OK, Tifton, GA, Vashti, TX, and Woodward, OK.

Experiment	Season	Frequency	Fall	Spring
Ardmore (AGR)	2015-2018	High	Every 4 weeks October-December	Every 2 weeks March-end of season
		Medium	Every 4 weeks November- December	Every 4 weeks March-end of season
		Low	Once in December	Every 6 weeks March-end of season
Ardmore (AGR)	2018-2020	High	Every 4 weeks October-December	Every 2 weeks March-end of season
		Medium	Every 8 weeks November-December	Every 4 weeks March-end of season
		Low		Once end of season
Ardmore (BRD)	2012-2014			Once end of season
Tifton	2012-2013			Once end of season
Vashti	2012-2014			Once end of season
Woodward	2012-2014			Once end of season

were intended to stimulate differences in forage growth over time to create varying biomass production for hyper-spectral sensor development.

Ardmore, OK (BRD)

The Ardmore, OK (BRD) site (34.11° N, 97.05° W; elevation 240 m), the soil type was Windthorst fine sandy loam (fine, mixed, active, thermic Udic Paleustalf). There were five cultivars of tall fescue including, the endophyte free Flechanil, in the 2012 to 2014 Ardmore (BRD) data. This site was managed as a yield trial harvested once in 2012, three times in the spring of 2013 from March to June, and once in the spring of 2014.

Woodward, OK

The Woodward, OK breeder site (36.25° N, 99.24° W; elevation 605 m; Carey silt loam [fine- silty, mixed, super active, thermic Typic Argiustoll]) was a tall fescue biomass yield study established on September 26th, 2011. The study focused on the summer-dormant varieties, including Flechanil. Harvests occurred once at the end of each season from 2012 to 2014.

Tifton, GA

The Tifton, GA breeder site (31.49° N, 83.53° W; elevation 118 m; Tifton loamy sand [fine-loamy, kaolinitic, thermic Plintic Kandiudult]) was composed of a variety of summer-dormant cultivars. The plots were seeded into a bermudagrass sod on November 11th, 2003 and managed as a cover crop until the trial began on November 2nd, 2011. Plots were harvested on April 2nd, 2012, and April 30th, 2013, and harvestable biomass yield was recorded.

Vashti, TX

The Vashti, TX site (33.55° N, 98.04° W; elevation 330 m; Anocon loam [fine, mixed, active, thermic Ultic Paleustalfs]), was a yield trial with the Noble Research Institute and was harvested once in 2012 on April 19th, twice in 2013 on April 4th and July 1st, and again on June 2nd, 2014.

Breeder Site Management

The breeder sites Ardmore, OK (BRD), Tifton, GA, Vashti, TX, and Woodward, OK had similar management. For all experiments, the plots were set up in 2011 in a randomized complete block design and were seeded using a Hege 500 plot drill at a rate of 17 kg ha^{-1} of seed into 7 rows. For the Ardmore (BRD), Tifton, and Vashti locations, there were 4 replications with 1.5 m by 6.1 m (5ft x 20ft) plots. Unlike the other breeder sites, Woodward had five replications and measured 1.5 by 7.6 m [5 by 25 ft; Trammell et al. (2018)]. For each of the breeder sites, there was a single application of ammonium nitrate (N–P–K, 34–0–0) at the rate of 46 kg N ha^{-1} at the time of sowing or early fall of each season. At the Ardmore (BRD) and Vashti sites, an application of 2,4-D (2, 4 D-dichlorophenoxyacetic acid) low volatile ester was applied at the rate of 1.12 kg a.i. ha^{-1} to control broad leaf weeds in the spring following establishment. Samples were collected using a sickle bar plot harvester at a height of approximately 7-cm.

3.3.3 Weather Data and DSSAT Location Files

Weather data near each location were obtained from the Oklahoma Mesonet (Brock et al., 1995; McPherson et al., 2007) and the University of Georgia Weather Network (Knox et al., 2020). Required weather inputs for the DSSAT model included daily maximum, minimum, and average, air temperatures, relative humidity, 2-meter wind speed, precipitation, and solar radiation.

DSSAT standard format weather files, as shown in Table 2.5, were written using the function `write_wth` from the DSSAT package (Phillip D. Alderman, 2020; Phillip D. Alderman, 2021).

Weather station metadata such as latitude, longitude, elevation, average daily temperature, temperature amplitude, the reference height for air temperature measurement, the reference height for wind speed, and average daily air CO2 were identified for each site. Daily weather data and weather station metadata were formatted as described in chapter 2 for DSSAT standard format weather files, and were written using the function `write_wth` from the DSSAT package (Phillip D. Alderman, 2020; Phillip D. Alderman, 2021).

3.3.4 Soil Data

Soil profile information at each site was obtained from the Soil Survey Geographical Database [SSURGO; Soil Survey Staff (2020)] based on the soil type and latitude and longitude of each location. This was then used to pull component- and horizon-specific soil property data. Estimates of model specific variables were determined for each location by using SSURGO reference values, deriving approximate equivalent values. The write_sol() function from the DSSAT version 0.0.4 R package (Phillip D. Alderman, 2020; Phillip D. Alderman, 2021) was used when writing soil input data to the DSSAT standard soil file format.

3.3.5 DSSAT-CSM Perennial Forage Model

The model being adapted for this study was a version of the DSSAT-CSM Perennial Forage Model parameterized for ryegrass [*Lolium spp.*; Oliveira et al. (2020)]. This model was chosen because ryegrass is a C3 cool- season perennial grass similar to tall fescue. Adaptations included setting several parameters to zero (RDRMG, RDRMM and RCHDP) to disable the effect of day length on inducing dormancy and setting

STRSRFL to 0 and STRLYR1 to 1 to position 100% of storage tissue in the first soil layer rather than on the soil surface. The parameter controlling maximum leaf-level photosynthetic rate (LFMAX) was also adjusted up to 1.41 based on results from Kiniry et al. (2018).

Simulation controls were set up to match the field conditions for each experiment at each different location. Simulations were initially set to mimic a rain-fed environment. In our analysis of observed and modeled biomass, the rain-fed environment experienced a vast amount of waterstress. Therefore, a set of counter-factual simulations were setup to explore the effect of waterstress on plant growth within the agronomic site. For these hypothetical simulations, automatic-irrigation was enabled when the top 10 cm of soil dropped below 90% available soil moisture.

3.3.6 Data Analysis

The relationship between measured and model estimated harvestable biomass yield was assessed using four goodness of fit statistics: root mean square error (RMSE), Willmott agreement index (d; Willmott, 1981), and Nash-Sutcliffe model efficiency (ME; Nash and Sutcliffe, 1970), and Relative Root Mean Square Error (rRMSE).

The statistical metrics were calculated as follows:

i) Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(y_n - \hat{y}_n)^2} \tag{3.3.1}$$

where, N = Total number of data points, y_n is the n^{th} observation (n=1,2,...N), and $\hat{y}_n$ is the predicted value for the n^{th} observation. Models with smaller values of RMSE are preferable.

ii) Willmott agreement index (d):

$$d = 1 - \frac{\sum_{n=1}^{N} (y_n - \hat{y}_n)^2}{\sum_{n=1}^{N} (|\hat{y}_n - \bar{y}| + |y_n - \bar{y}|)^2} \tag{3.3.2}$$

where, N, y_n, and $\hat{y}_n$ are as described above, and $\bar{y}$ is the average of the observed data points. This statistic ranges between 0 to 1 with values closer to 1 indicating good model fit.

iii) Nash-Sutcliffe Efficiency (ME):

$$ME = 1 - \frac{\sum_{n=1}^{N} (y_n - \hat{y}_n)^2}{\sum_{n=1}^{N} (y_n - \bar{y})^2} \tag{3.3.3}$$

where, N, y_n, $\hat{y}_n$, and $\bar{y}$ are as described above. The values of ME can range from $-\infty$ to 1 and values closer to 1 indicate a better-fitting model.

iv) Relative Root Mean Square Error (rRMSE):

$$rRMSE = \frac{RMSE}{\bar{y}} \tag{3.3.4}$$

where, $RMSE$ and $\bar{y}$ are as defined above. Models with smaller values of rRMSE are preferable.

3.4 Results and Discusion

In evaluation of the model, it was determined that the simulated harvestable biomass was not aligning adequately with the observed data. In an analysis of the agronomic site over all seasons, harvest frequencies, and nitrogen levels comparing simulated harvestable biomass to observed yield collected in the field at Ardmore (AGR), the model was unable to adequately predict harvestable biomass of tall fescue with a Willmott agreement index (D) of 0.63, a Nash-Sutcliffe model efficiency (ME) of 0.02,

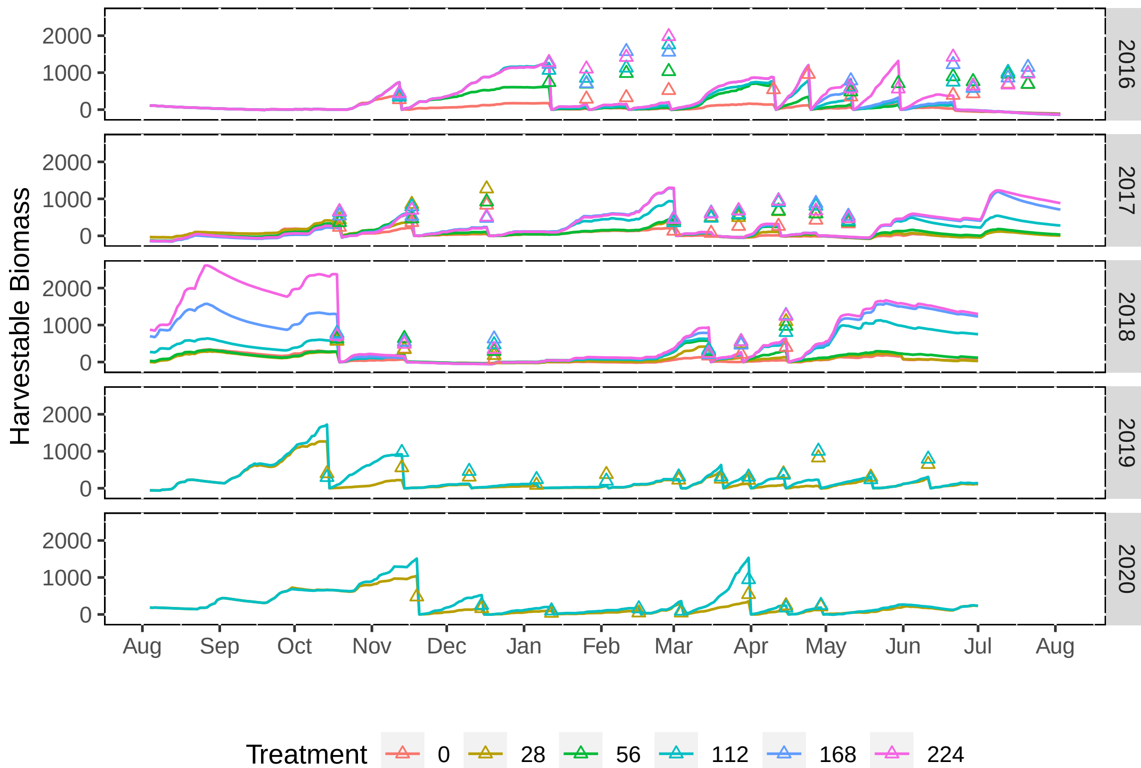

Figure 3.1: Modeled harvestable biomass (kg ha^{-1}) over time for Ardmore, OK (AGR) from 2015 – 2020 at a high harvest frequency, where the lines represent the simulated data, the points are the observed data, and the colors denote the different nitrogen levels.

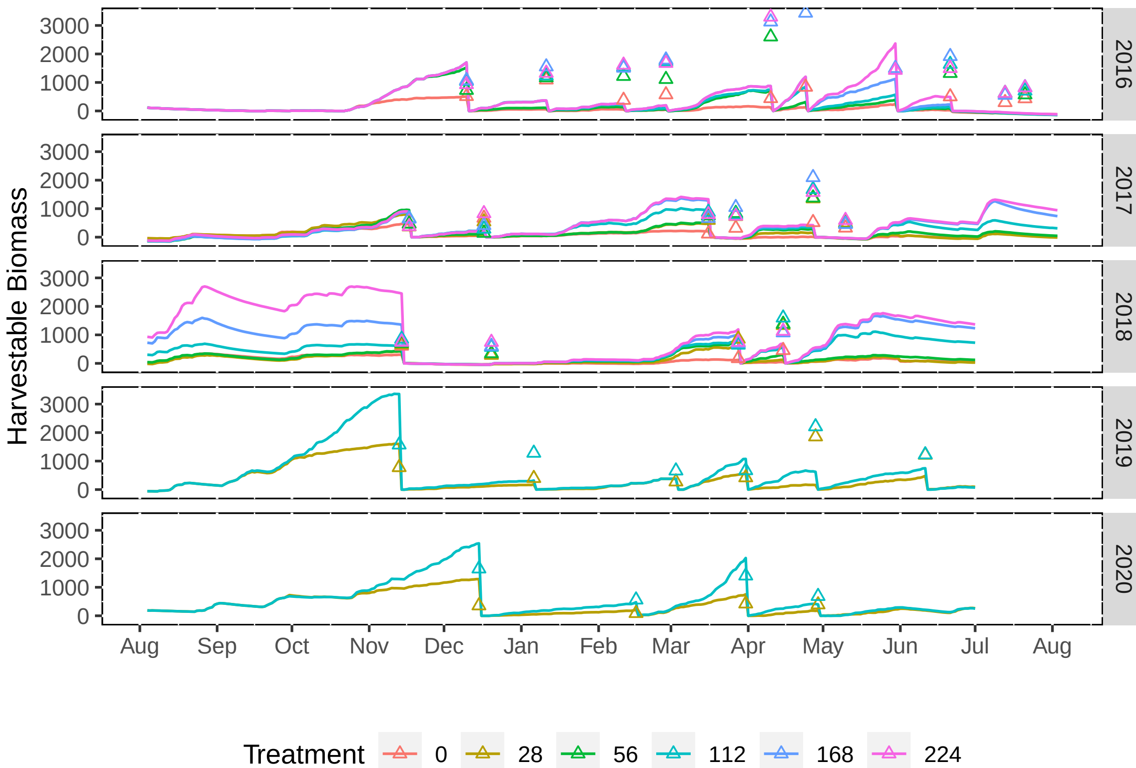

Figure 3.2: Modeled harvestable biomass (kg ha^{-1}) over time for Ardmore, OK (AGR) from 2015 – 2020 at a medium harvest frequency, where the lines represent the simulated data, the points are the observed data, and the colors denote the different nitrogen levels.

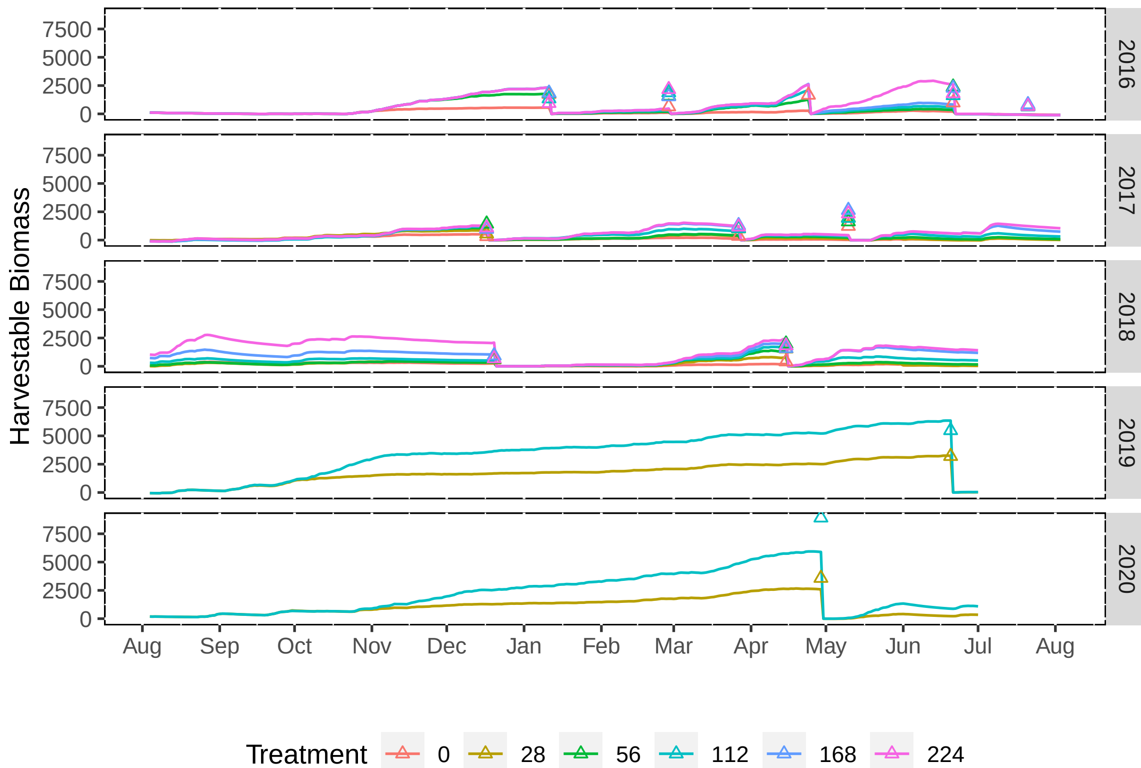

Figure 3.3: Modeled harvestable biomass (kg ha^{-1}) over time for Ardmore, OK (AGR) from 2015 – 2020 at a low harvest frequency, where the lines represent the simulated data, the points are the observed data, and the colors denote the different nitrogen levels.

and a root mean squared error (RMSE) of 5124 (Fig. 3.1). Overall, harvestable biomass was under-predicted with a mean bias of -376 kg ha^{-1}.

Each of the time-series plots represent total harvested biomass at Ardmore (AGR) from 2015-2020 at differing harvest frequencies, high (Figure 3.1), medium (Figure 3.2), and low (Figure 3.3). This represents the total harvestable biomass and does not account for the 760 kg ha^{-1} of residual biomass that would remain. At each harvest frequency, the figures depict that simulated biomass was strongly over-predicted in the fall leading into the winter dormant season and was rather consistently under-predicting harvestable biomass in the rest of the season. This trend was constant across all seasons. There were some suspicious values in the observed data, namely the outliers found in April of 2016. Another unusual feature of the dataset was the harvest on July 22^{nd} which is typically out of season for tall fescue. It is suspected that high rainfall in May and June prevented the stand from going dormant.

Figure 3.4 supports the argument that the model was under-predicting biomass at the agronomic site due to waterstress, as evidenced by those dates where there was growth in the observed data when the model output suggests that soil moisture has been exhausted. For example from February to April in 2016 and from March to May in 2017, the points where the model was severely under predicting biomass, there was a larger amount of waterstress. However, this cannot be the only issue because there were also times like in December of 2017 when the observed biomass was much higher than the simulated biomass, yet there was no presence of waterstress.

Unlike the agronomic site, the modeled harvestable biomass for the breeder sites, Ardmore (BRD), Tifton, Vashti, and Woodward was over-predicted when compared to the observed data collected at each location with a mean bias of 664 kg ha^{-1}.

Figure 3.5 indicates that the model was unable to predict harvestable biomass at the breeder sites: Ardmore (BRD), OK, Tifton, GA, Vashti, TX, and Woodward, OK (D = 0.61, ME = -1.06, and RMSE = 2408). Woodward experienced the lowest biomass

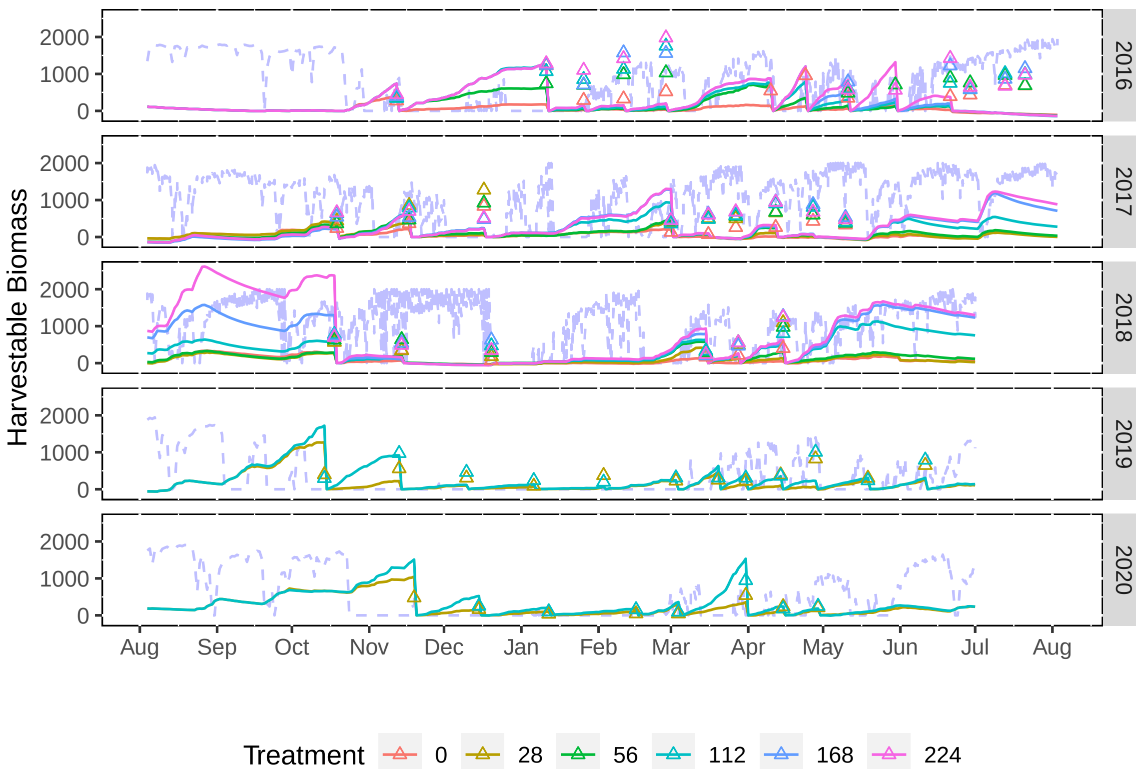

Figure 3.4: Modeled harvestable biomass (kg ha^{-1}) over time for Ardmore, OK (AGR) from 2015 – 2020 at a high harvest frequency with waterstress x 2000, where the soild-lines represent the simulated data, the translucent- dotted-line is modeled waterstress, the points are the observed data, and the colors denote the different nitrogen levels.

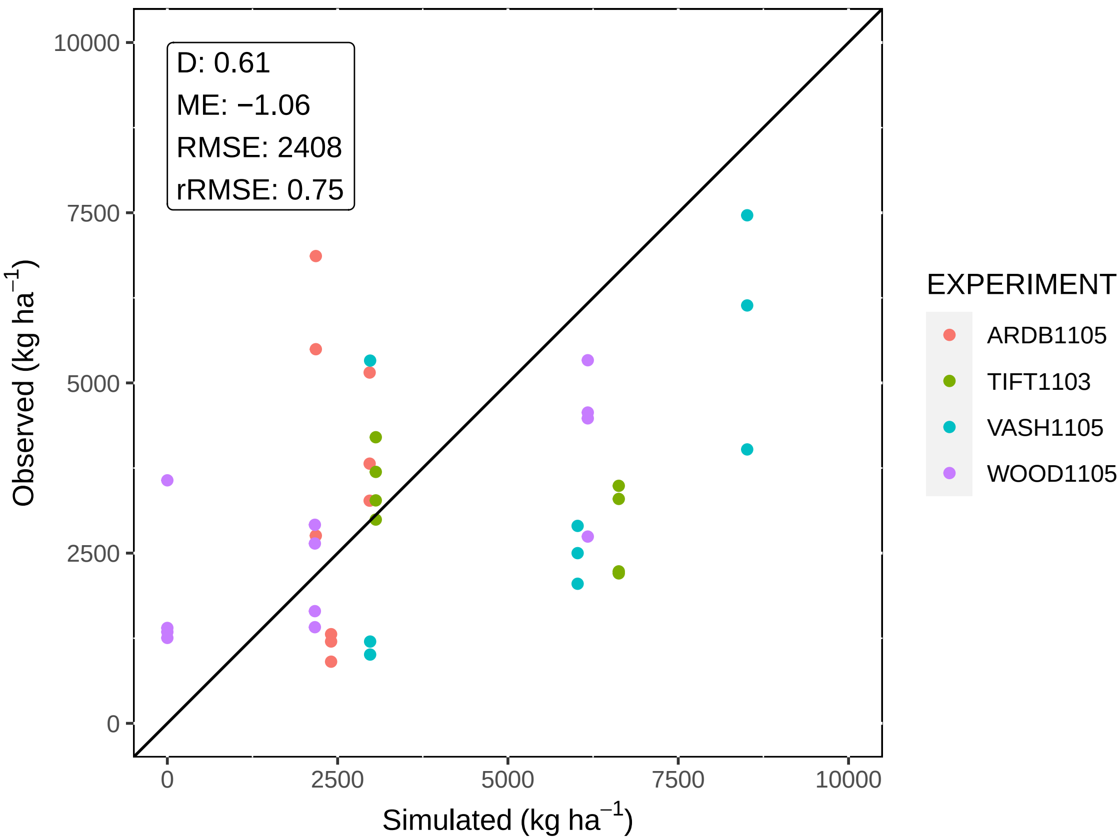

Figure 3.5: Comparing simulated and observed harvestable biomass (kg ha^{-1}) for the Breeder sites at Ardmore, OK (BRD), Tifton, GA, Vashti, TX, and Woodward, OK, where colors represent the different location and the points are harvestable biomass (kg ha^{-1}.

on average possibly due to low rainfall and harsh temperatures. These environmental conditions did affect the observed values at the Woodward site, but the simulated harvestable biomass experienced a freeze event which caused termination of the model in January of 2014 resulting in the date with 0 kg ha^{-1} of modeled biomass.

When comparing the observed and simulated harvestable biomass, the Tifton, GA site was relatively accurate in the first season, in 2012, but over-predicted in 2013, contributing to the overall mean bias. From March to July, during the peak growing season, 2013 experienced nearly twice as much rain as in 2012, with 576 mm from March to July of 2012 and 1080 mm from March to July of 2013. It is possible the soil properties at the Tifton site were different from the soil properties provided from SSURGO. The model may be over-predicting biomass in 2013 because it does not have site specific soil inputs which accurately predict the water holding capacity of the soil.

The Vashti, TX site showed an over-prediction of simulated biomass. This over-prediction could stem from non-site specific weather data. The weather station used for Vashti, TX was the Waurika Mesonet station (WAUR). This was the closest publicly available weather source that provided the information needed for the dynamic crop model and it was approximately 70 km (44 mi) from the Vashti site.

There could be several explanations for why the model was poorly-predicting biomass. In future analysis, evaluation should be conducted on the distribution of biomass above- and below-ground. Excluding conditions where there was no above-ground biomass, the model predicted above- to below-ground partitioning on average to be between 1 and 2.5, across all sites, which is lower than expected. Typically in grasses, approximately 80%–85% of plant biomass is partitioned to above-ground organs, and 15% – 20% is allocated to roots (Irving, 2015).

One constraint of the data was that the model was simulating total above-ground biomass; however, the dataset was only harvestable biomass. Assumptions were made about how much un-clipped biomass remained (residual stubble) and how much was actually being harvested (harvestable biomass). After the sample was cut, the forage mass kg ha^{-1} remaining under the cutting bar had to be determined using the clipping height. A conversion from clipping height to forage mass in km ha^{-1} (Rayburn and Lozier, 2003) was used to calculate the residual biomass at each the agronomic site and the breeder sites. The residual amount calculated for Ardmore (AGR) data was 760 kg ha^{-1}, and for the breeder sites, 1800 kg ha^{-1}. In analysis, the calculated residual amount was subtracted from the simulated biomass so that both the measured and modeled values were estimating harvestable biomass. This action was performed to mimic a pasture grazing or mowing scenario where residual is usually left standing to cause quicker regrowth (Deléglise et al., 2015; Hannaway et al., 1999). The error could be that the residual prediction was inaccurate, therefore causing an inconsistent prediction in modeled biomass. These residual stubble mass variables were assumed to be constant (i.e. not varying by season or management), which may not reflect reality. It is likely that all of these factors could affect the residual stubble mass in the field.

Conversely, the calculated estimate for residual biomass could have been correct and the model was not estimating the total biomass production properly, thus low simulated biomass was produced due to under-estimation of the photosynthetic capacity of the canopy. If this was the error, the maximum leaf photosynthesis rate (LFMAX) parameter could be adjusted up from 1.41 (Kiniry et al., 2018) to a level that increases overall productivity of the plant to fit the observed data.

Though adjustments may need to be made in the parameterization of the model, there were also uncertainties in the inputs, specifically the soil data. We are confident in the weather data provided due to the standardized protocols of the Oklahoma Mesonet (McPherson et al., 2007; Brock et al., 1995) and the University of Georgia Weather Network (Knox et al., 2020). We have less confidence in the soil data from each site.

Although we expect the general characteristics of soil data pulled from SSURGO to be representative of the soil types at each location, it is possible that, in reality, the site-specific soil properties deviated from the general properties captured by SSURGO. If the actual soil water holding properties were substantially different from the SSURGO data, it would help explain the presence of simulated waterstress even when the observed data did not appear to indicate such a limitation on growth. For instance, in Figure 3.4 there was still growth in the observed values, even when the model was suggesting that soil moisture had been completely exhausted. This indicated a soil moisture issue, because it is impossible to have plant growth without adequate soil moisture. Nevertheless, the biomass data suggest that there was at least enough soil moisture to have biomass because, in the clipped data, growth continued.

If the constraint were soil moisture, the assumption was, when a hypothetical irrigation simulation was enabled in simulation controls to alleviate waterstress, there would be a dramatic increase in productivity for those cases where there was observed biomass growth even when the model under-predicted biomass due to waterstress. However, Figure 3.6 indicates that even when a modeled irrigation scenario is introduced, the model still under-predicts biomass compared to the observed data.

Figure 3.6 represents the difference in a modeled waterstressed scenario and a modeled auto-irrigated scenario with a nitrogen application of 112 kg ha^{-1} to alleviate any nitrogen stress that may be present. It is evident, in Figure 3.6, that waterstress is part of the issue; however, because the simulated harvestable biomass under waterstressed conditions outperforms the irrigated harvestable biomass, there are other contributing factors.

Whether in a simulated irrigated or waterstressed environment, the model was accurate in simulating the separation in the different nitrogen treatments within the model and what was observed in the field. Not only was the model correct in predicting

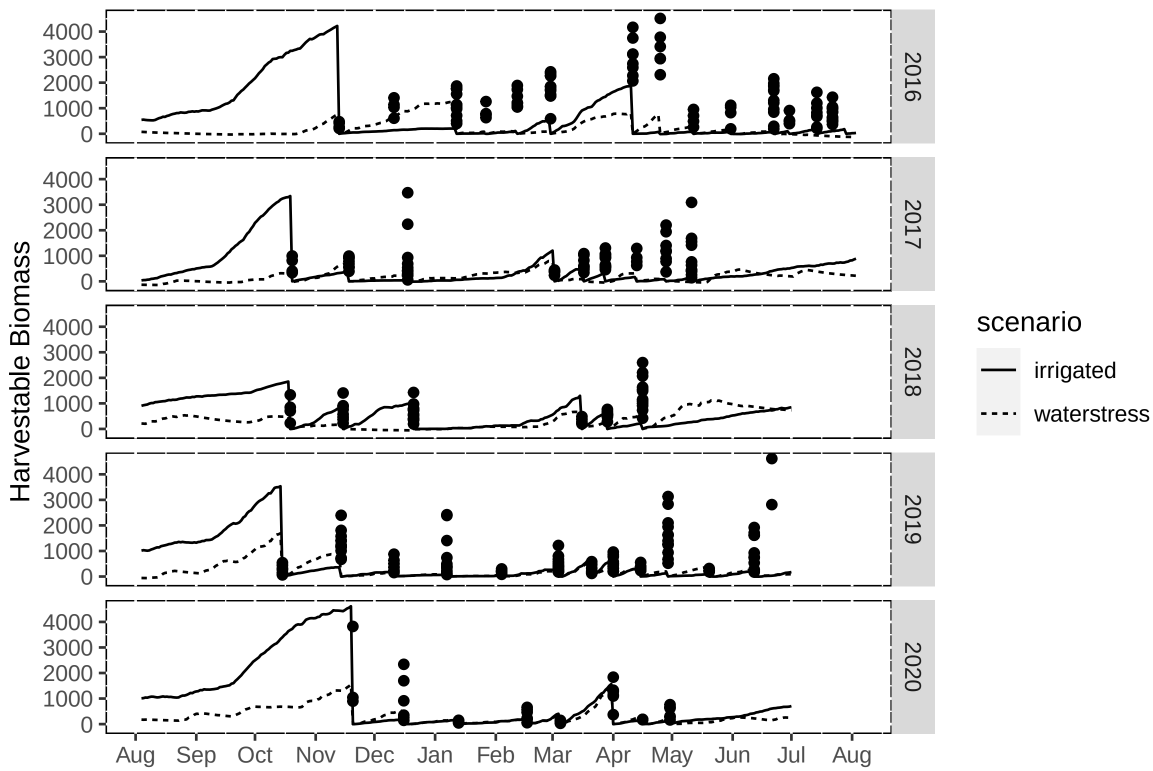

Figure 3.6: Modeled harvestable biomass (kg ha^{-1}) over time for Ardmore, OK (AGR) from 2015 – 2020 at a high harvest frequency comparing model simulated auto-irrigated and waterstressed scenarios at 112 kg ha^{-1} N, where the solid-line represents the irrigated scenario, the dotted-line is the waterstressed scenario, and the points are the measured values.

the separation between treatments, but it was also correct separating them in the same orders of magnitude between the levels (Fig. 3.7).

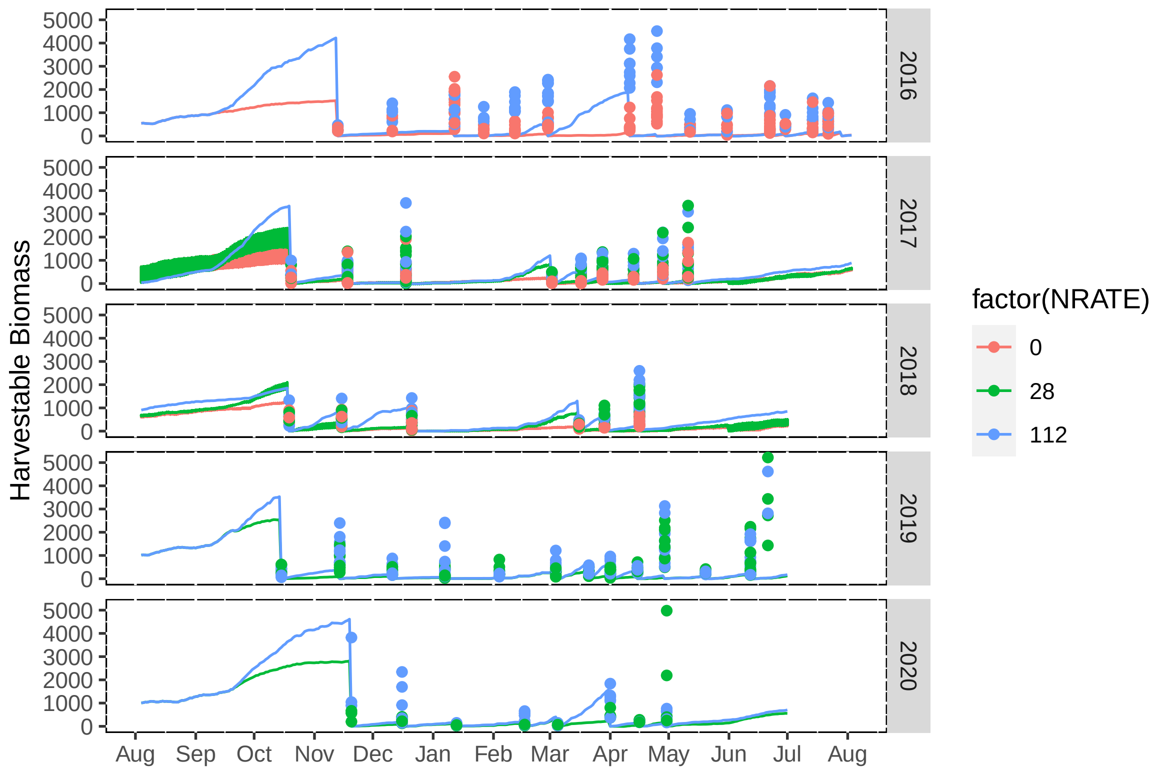

Figure 3.7: Modeled harvestable biomass (kg ha^{-1}) over time for Ardmore, OK (AGR) from 2015-2020 at a high harvest frequency comparing model simulated auto-irrigated and waterstressed scenarios at 3 levels of N: 0, 28, 112 kg N ha^{-1} where the line is the simulated data, the points are the measured data, and color represents the nitrogen level.

It is not clear why the simulated data did not align with the observed data; it could be any of the explanations discussed: inaccurate residual biomass assumption, LFMAX value, above- to below-ground partitioning, or incorrect input data leading to a waterstress issue. The model shows an appropriate qualitative response to simulated waterstress and nitrogen response, but the model may be incorrect in its prediction of the intensity of waterstress present and, consequently, may be quantitatively inaccurate.

For the model to provide more accurate predictions of harvestable biomass, further adaptations of more parameters are needed, such as those which control above- to below-ground partitioning, response to temperature (Insua et al., 2019), and maximum leaf photosynthesis rate. Calibration of parameters and following through with this analysis on a larger, more thoroughly documented dataset would likely result in quantitative estimates which more accurately predict the harvestable biomass of tall fescue in the southern Great Plains.

3.5 Conclusion

Tall fescue is an increasingly important grass for ranchers in the SGP for its variety of uses on the land for livestock and wildlife, as well as for its environmental and economic impact. Anticipating harvestable biomass of forage is important for ranchers trying to sustain the longevity of their land and reach optimal productivity of their livestock. We adapted an existing DSSAT-CSM-Perennial Forage Model for perennial ryegrass to achieve statistical predictions and developed a model to predict harvestable biomass of tall fescue. The current state of the model accurately simulates the separation in differing nitrogen treatments when comparing modeled and observed yield and separates the nitrogen levels at the correct levels of magnitude. However, the model is not yet quantitatively accurate possibly due to lack of site-specific soil input data, inaccurate assumptions about residual stubble mass or poor parameterization. The model, in its current state, is not yet ready for ranchers. Further model development work should focus on better parameterization and acquiring additional datasets that are thoroughly documented.

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CHAPTER IV

GENERAL CONCLUSIONS

Tall fescue is an increasingly important grass for ranchers in the southern Great Plains (SGP) for its variety of uses on the land for livestock and wildlife, as well as for its environmental and economic impact. Anticipating harvestable biomass of forages is important for ranchers trying to sustain the longevity of their land and reach optimal productivity of their livestock. There has been little research in the area of tall fescue modeling (Kiniry et al., 2018). The limited research is due in part to few long-term forage trials with the ideal characterization needed for modeling.

In this thesis we adapted an existing DSSAT-CSM-Perennial ryegrass model for estimating forage biomass of tall fescue in the southern Great Plains. The DSSAT-CSM-Perennial forage model, a dynamic crop model, requires management, weather and soil input data to predict plant growth. Model evaluation depends on the availability of observed biomass data. For this project, focus was put on compiling one comprehensive dataset in DSSAT standard file format for observed biomass (FileT), management data (FileX), weather data (.WTH), and soil data (.SOL) from a range of environments that will permit further model development, parameterization and evaluation. Biomass data were compiled from five different experiments across four different locations, Ardmore, OK, Tifton, GA, Vashti, TX, and Woodward, OK in association with the Noble Research Institute. The Soil Survey Geographical Database [SSURGO; Soil Survey Staff (2020)] was used as the data source for each site. Daily weather data and weather station metadata were obtained from the Oklahoma Mesonet (McPherson et al., 2007; Brock et al., 1995) and the University of Georgia Weather

Network (Knox et al., 2020). The data for all locations and growing seasons were merged to generate the curated dataset.

Using the adapted model with the combined dataset, we evaluated model performance in terms of harvestable biomass. There were positive results when simulating the effects of nitrogen treatments on harvestable biomass. Specifically, the model was correct in predicting the magnitude of N response across treatment levels. However, model performance was inconsistent in predicting seasonal differences in biomass production. The model is under-predicting harvestable biomass for the agronomic site, Ardmore (AGR), with a mean bias of -376 kg ha^{-1}, and it is over-predicting for the breeder sites with a mean bias of 664 kg ha^{-1}. The model was not able to adequately predict harvestable biomass of tall fescue for either the breeder data (D = 0.61, ME = -1.06, and RMSE = 2408) or the agronomic data (D = 0.63, ME = 0.02, and RMSE = 5124).

Though this model can not yet adequately predict tall fescue harvestable biomass, the curated dataset described in Chapter 2 is necessary for analysis to be conducted and parameter changes to be tested as described in Chapter 3. A large portion of this project went into data collection and cleaning. There is potential for this curated dataset to aid in calibration during future parameterization of the model. The analysis in Chapter 3 would benefit from more site-specific information, especially within the soil data. The model would also benefit from additional sites with more comprehensive characterization of inputs. Future directions for this research would be to achieve better parameterization through calibration of parameters that control above- to below-ground partitioning, response to temperature, and maximum leaf photosynthesis rate.

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