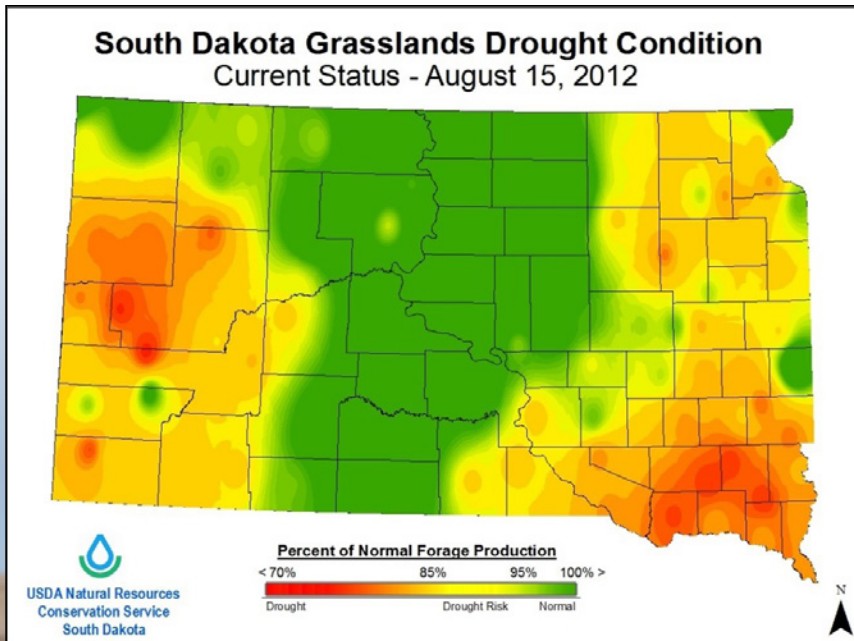
Forest Service
U.S. DEPARTMENT OF AGRICULTURE

Rocky Mountain Research Station | RMRS-GTR-447 | September 2025

The South Dakota Drought Tool: Current Model and Validation

Jacqueline P. Ott, Stanley Boltz, Shannon Kay, Emily Helms-Rohrer



Ott, Jacqueline P.; Boltz, Stanley; Kay, Shannon; Helms-Rohrer, Emily. 2025. **South Dakota drought tool: Current model and validation**. Gen. Tech. Rep. RMRS-GTR-447. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 53 p. https://doi.org/10.2737/RMRS-GTR-447

Cover: The South Dakota Drought Tool depicting where forage production would be reduced within the State. Cows near Hay Canyon experimental site on the Buffalo Gap National Grassland. USDA Forest Service photo by Erika Reiter.

Abstract

Drought often occurs when precipitation is lower than average growing season precipitation. Drought can vary spatially and temporally across the Northern Great Plains and lead to localized as well as widespread reductions in forage production. In South Dakota, because of its extensive grasslands, managers and producers rely on drought prediction tools that can forecast drought and be frequently updated as the growing season progresses. The Natural Resources Conservation Service (NRCS) developed the South Dakota Drought Tool (SDDT) to provide peak and monthly forage production estimates for the entire State. The SDDT uses precipitation measurements to calculate these production estimates. The objectives of this work were to:

1. Formally describe the current SDDT model.
2. Confirm the best model fit of precipitation data used in the SDDT to predict percent of average peak forage production using National Resources Inventory data.
3. Evaluate how well the model is estimating the July peak forage, on a monthly basis starting the previous November through July, using National Resources Inventory data (i.e. evaluate the uncertainty around the peak forage predictions).
4. Evaluate the best model fit of the SDDT precipitation model for monthly forage predictions using National Resources Inventory data (i.e., evaluate how well the SDDT predicts forage production in real time).

The SDDT model was originally based on the Cole model that calculated forage production based on the annual precipitation from the current and previous years. The SDDT model builds on this concept but adds in a threshold for limiting maximum monthly precipitation (hereafter referred to as critical values) and two seasonal factors to weight spring and fall precipitation. The SDDT model uses near-real-time precipitation data from over 200 weather stations Statewide to update their estimates monthly. This model is mathematically described, and a written example of how the SDDT calculates its forage production predictions is provided. The SDDT model and output are available as an interactive Microsoft Excel© file that is accessible for all users. Model output is also used by NRCS to develop statewide drought condition maps that are updated monthly. Producers and managers actively use the SDDT.

To validate the peak and monthly forage production estimates of the SDDT, a combined National Resources Inventory (NRI) and U.S. Department of Agriculture, Forest Service dataset provided 1,051 measurements of forage production across South Dakota between 2003 and 2019. Each forage measurement was paired with the closest weather station used by the SDDT. Peak and monthly SDDT forage production predictions were calculated for each ground measurement. For objective two, we optimized the parameters of the SDDT for peak forage production including the spring and fall precipitation weighting factors and precipitation critical values. Overall, model optimization did not greatly improve the original SDDT estimates, but did improve estimates for loamy soil ecological sites. Uncertainty for peak production was +/-48 percent and did not differ between the Black Hills and the rest of the State. For objective three, model error was similar across months indicating that model estimates did not become more certain as peak production neared. For objective four, optimization improved the real-time predictions of the SDDT. Error associated with real-time predictions was similar to the error of associated peak production estimates and the predictions maintained an error of +/– 59 percent after optimization.

The high error rate of the model is due to multiple factors, including uncertainty due to the baseline reference values of long-term forage production obtained from the Ecological Site Descriptions, the distance between forage measurements and their nearest weather station, and measurement error introduced during the forage clipping process of the NRI data. The SDDT users have often remarked on how the SDDT predictions reflect their observed forage production. The most likely source of error is from unrefined reference values of long-term forage production at each location. To confirm this hypothesis, proper reference values for each datapoint would need to be estimated and could be done by re-evaluating the community states and phases of the NRI data, repeating forage sampling at the same location over multiple years, or by using satellite data to inform long-term productivity of a site. To make the model more useful and defensible in the future, model assumptions could be tested using variable selection. The SDDT is one of the only drought tools that aids managers in creating a drought contingency plan and will likely continue to be used by many of South Dakota’s producers.

Keywords: drought, forage, productivity, range management

Authors

Jacqueline P. Ott is a Research Ecologist with the U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station in Rapid City, South Dakota.

Stanley Boltz† was Regional Soil Health Specialist with the U.S. Department of Agriculture, Natural Resources Conservation Service, Huron, South Dakota.

Shannon Kay is a Statistician with the U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, in Fort Collins, Colorado.

Emily Helms-Rohrer is a State Rangeland Management Specialist with the U.S. Department of Agriculture, Natural Resources Conservation Service, in Rapid City, South Dakota.

†Deceased [18 Sep 2024]

Acknowledgments

We thank the Natural Resources Conservation Service, Rocky Mountain Elk Foundation, Black Hills National Forest, Nebraska National Forest and Grassland, South Dakota Game Fish and Parks, and Rocky Mountain Research Station for financial support to conduct the validation and writing of this report. Mark Vedder (BHNF) and Shelly Deisch (SDGFP) provided helpful guidance during the formation of the project. Krista Ehlert (South Dakota State University) and Matt Reeves (RMRS) provided meaningful reviews of this work.

In memoriam

We dedicate this publication to Stan Boltz for his dedication and leadership in rangeland management in South Dakota and the greater northern Great Plains region. This drought tool was conceived and implemented by Stan to enable managers to better predict drought conditions in the State of South Dakota. As he was able to easily relate the model to on-the-ground practical measurements, this tool made a lot of sense to land managers and was readily adopted throughout the State. Stan will be missed by many in the rangeland community.

This page intentionally left blank.

Contents

This page intentionally left blank.

Introduction

Drought in the Northern Great Plains of South Dakota

Drought occurs when water is limited in an ecosystem and precipitation drops below the average monthly or annual precipitation. Droughts can last for a few weeks, months, or even years (Luce et al. 2016). Because of the cold winters and hot summers in the Northern Great Plains (NGP) and the dominance of cool-season (C_3) grasses in most of the central and western portions of South Dakota (SD), the primary growing season occurs during the spring and summer with fall rains influencing the subsequent calendar year's growth through fall seed germination and resprouting of perennial herbaceous plants (Epstein et al. 1997; Teeri and Stowe 1976). When precipitation drops below average during any part of the growing season or when temperatures are warmer than normal and cause increased evapotranspiration, vegetation growth can be reduced. This results in reductions in forage and water availability to wildlife and livestock (agricultural and hydrologic drought). As livestock and hunting are major components of the economy of these grasslands, drought can have impacts at local, regional, and national scales (Conant et al. 2018).

Drought in the NGP can vary spatially and temporally. The NGP climate is known to have significant interannual variability in annual precipitation (fig. 1). Within each annual growing season, there can also be great variability in the distribution of precipitation. Climate change is predicted to increase the number of heavy precipitation events, concentrating rainfall in short bursts (Conant et al. 2018). In mesic (i.e. wetter) grasslands, such as the tallgrass prairie of eastern South Dakota, longer dry intervals between precipitation events can lead to extended periods of below-average soil water content, resulting in plant stress and declines in forage production (Heisler-White et al. 2009; Knapp et al. 2008). In more arid grasslands, such as those located in western South Dakota, larger rainfall events can increase periods of above-average soil water content and increase forage production (Knapp et al. 2008; Heisler-White et al. 2009). Furthermore, previous year precipitation can have differing effects on forage production dependent on if it was above or below average (Knapp et al. 2017). Drought can also be spatially variable, and drought status can vary within a State as well as across States (fig. 2). Forage and water level reductions can be observed in localized geographic areas or across wide expanses of South Dakota depending on precipitation and temperature patterns.

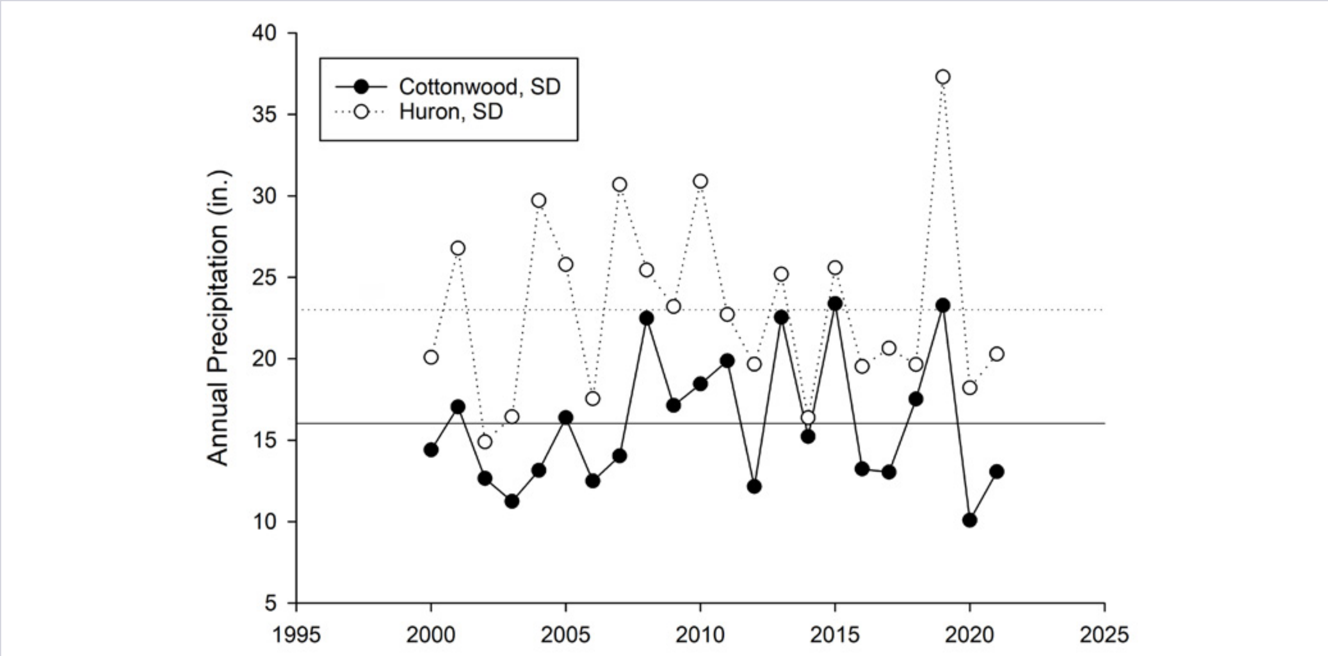


Figure 1—Annual precipitation from 2020 to 2021 in the semi-arid prairie of Cottonwood and the temperate prairie of Huron, in South Dakota. The mean annual precipitation—shown as horizontal reference lines—is 16.03 in for Cottonwood and 23.02 in for Huron.

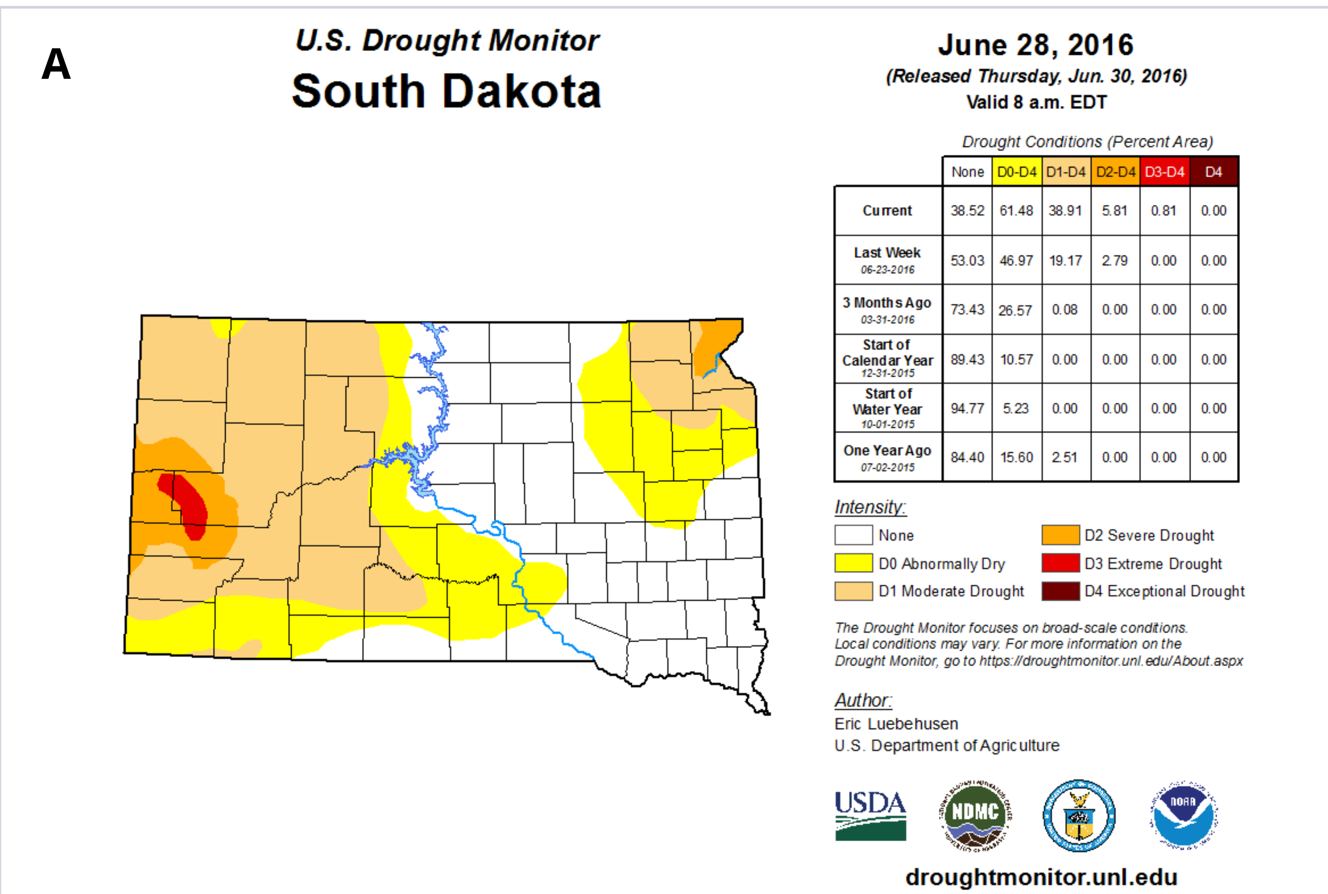


Figure 2—(A) U.S. Drought Monitor for South Dakota in late June 2016. Note that South Dakota has areas of no drought as well as moderate and even extreme drought.

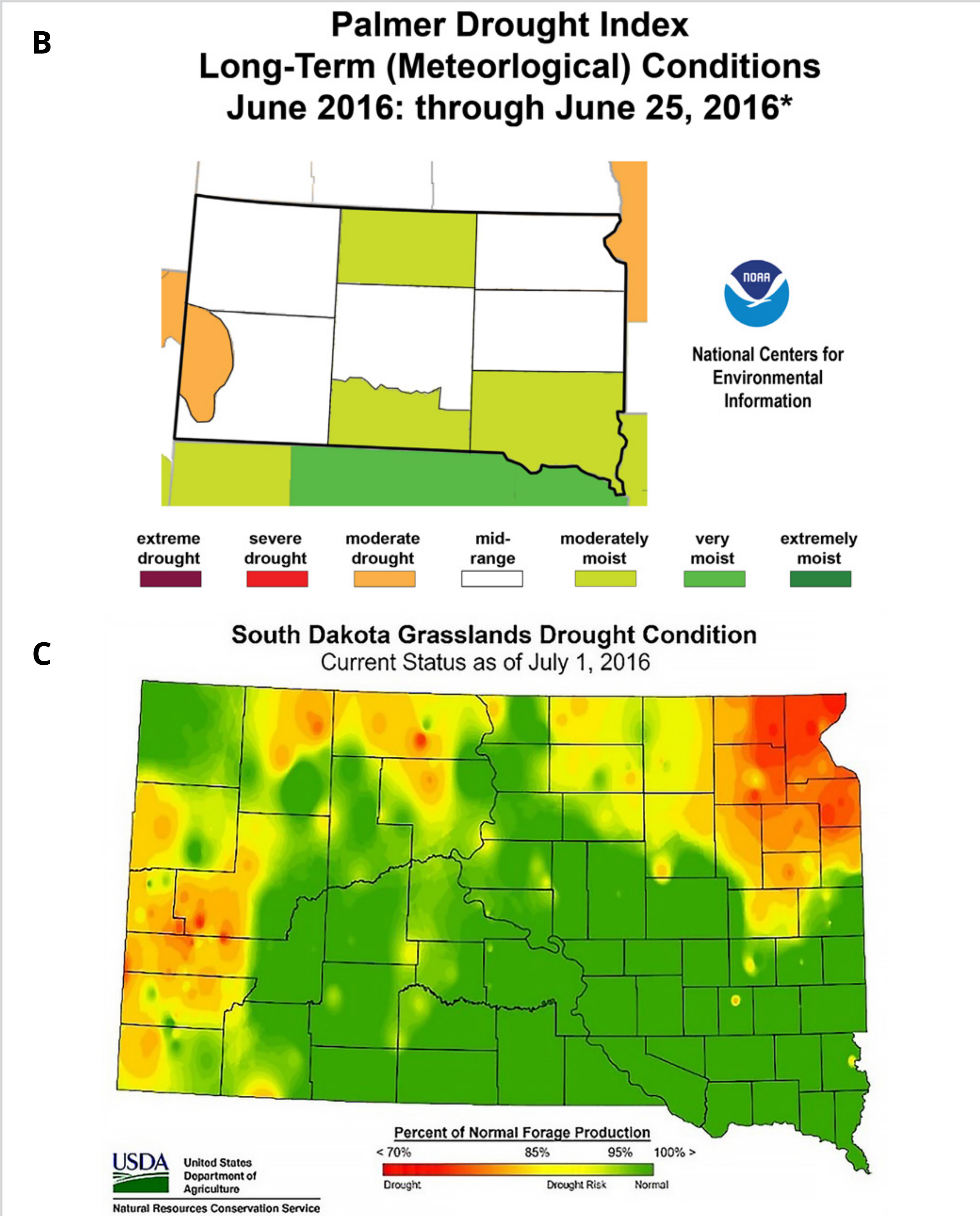


Figure 2—(B) Palmer Drought Index for South Dakota in late June 2016. (C) South Dakota Drought Tool Map for July 1, 2016. Note: South Dakota has areas of moderate drought, no drought, and moderately moist conditions.

Historically, drought has significantly impacted the lives of Great Plains inhabitants in South Dakota. From 1887 to 1896, a series of years with below-average precipitation caused severe reductions in grass production (Hoyt 1936). The years 1893 and 1894 were especially dry in widespread areas of the NGP. Some recovery occurred in 1891–1892, but the gains in forage productivity made in 1892 were likely diminished by localized outbreaks of the Rocky Mountain locust (Lockwood and Debrey 1990). While the drought of the early 1930s did not last as long and did not have the added perturbation of the locust, its severity during 1938–1939 was greater compared to the 1890s drought (Hoyt 1936). Grassland species composition shifted—more mesic grasses disappeared, and more arid grasses expanded eastward (Albertson and Weaver 1946; Weaver and Byrd 1943).

Dramatic reductions in forage also occurred during the 1966 drought (Hanson et al. 1978). Since the year 2000, the U.S. Drought Monitor was used to assess drought conditions and rank their severity (D1–D4) across the United States (National Drought Mitigation Center 2025). Based on assessments, the longest drought duration in South Dakota lasted 349 weeks, beginning on December 4, 2001, and ending on August 5, 2008. The most intense period of drought occurred the week of October 9, 2012, when the highest level of drought (D4) affected 32.57 percent of South Dakota (NOAA National Integrated Drought Information System 2022).

South Dakota Drought Tool (SDDT)—Purpose and Need for Model Validation

Predictions of drought impacts on forage production assist managers and producers in planning for reduced forage and water resources. Managers need tools that can be frequently updated as the growing season progresses. Weekly updates of drought predictions help managers understand the status of their rangelands in real-time as they reach different decision points during the growing season. Critical decision dates (i.e., trigger dates) for drought management need to occur in the spring, as April to June precipitation is the period most closely correlated with annual forage production in the NGP (Smart et al. 2021).

To aid in Statewide drought planning, the NRCS developed the SDDT for grasslands. Using precipitation data, the SDDT predicts peak forage production estimates for the entire State. Its interactive interface allows users to enter their own local precipitation data or use precipitation measurements from nearby weather stations. The SDDT also provides a template for producers to develop a drought contingency plan. The NRCS generates Statewide maps of the grassland drought conditions throughout the growing season and provides them monthly.

The SDDT model has estimated changes in forage that coincide with visual observations and experiences in South Dakota. Additionally, the NRCS has collected forage data across the State as part of the National Resources Inventory (NRI). The NRI data from 2003 through 2010 have been used to determine variable coefficients (i.e., weights) using Microsoft Excel© formulas in the SDDT model. However, further validation with more robust algorithms to determine variable coefficients and a longer-term dataset (2003–2016) could improve the SDDT predictions of forage production across the State. This effort would help producers understand how well the SDDT predicts forage and where further development of the SDDT should be directed. There is also a need to formally describe the SDDT model that will benefit its current users and future revisions of the model. By having the equations of the model described, users will be able to understand how the model currently functions, and future modelers can build upon the equations for future models. Therefore, our objectives were to:

1. Formally describe the current SDDT model.
2. Confirm the best model fit of precipitation data used in the SDDT to predict percent of average peak forage production using NRI data. (Validation Objective 1)
3. Evaluate how well the model estimates peak forage in November of the year prior through July of the year of prediction using NRI data (i.e., evaluate whether the uncertainty around the peak forage predictions diminishes as we approach the time of peak forage). (Validation Objective 2)
4. Evaluate the best model fit of the SDDT precipitation model for monthly forage predictions (i.e., evaluate how well the tool predicts percent of forage production in near-real time. (Validation Objective 3)

Climate of South Dakota

The Great Plains cover the central portion of the United States and extend into southern Canada. South Dakota is within the Northern Great Plains (NGP) and primarily supports semi-arid, northern mixed-grass prairie with some temperate tallgrass prairie in its eastern third and ponderosa pine forests in the Black Hills at its western edge (fig. 3), U.S. Environmental Protection Agency 2010). Temperatures are fairly consistent across the State, but precipitation is greater in the eastern part of the State and in the Black Hills due to topography in the western part of the State (figs. 4, 5). The climate has seasonal aridity patterns with approximately 48 percent of annual precipitation occurring in late spring and early summer (May–July) and less than 11 percent of annual precipitation occurring in the winter (November–February; see Supplementary Material S1 and S2).

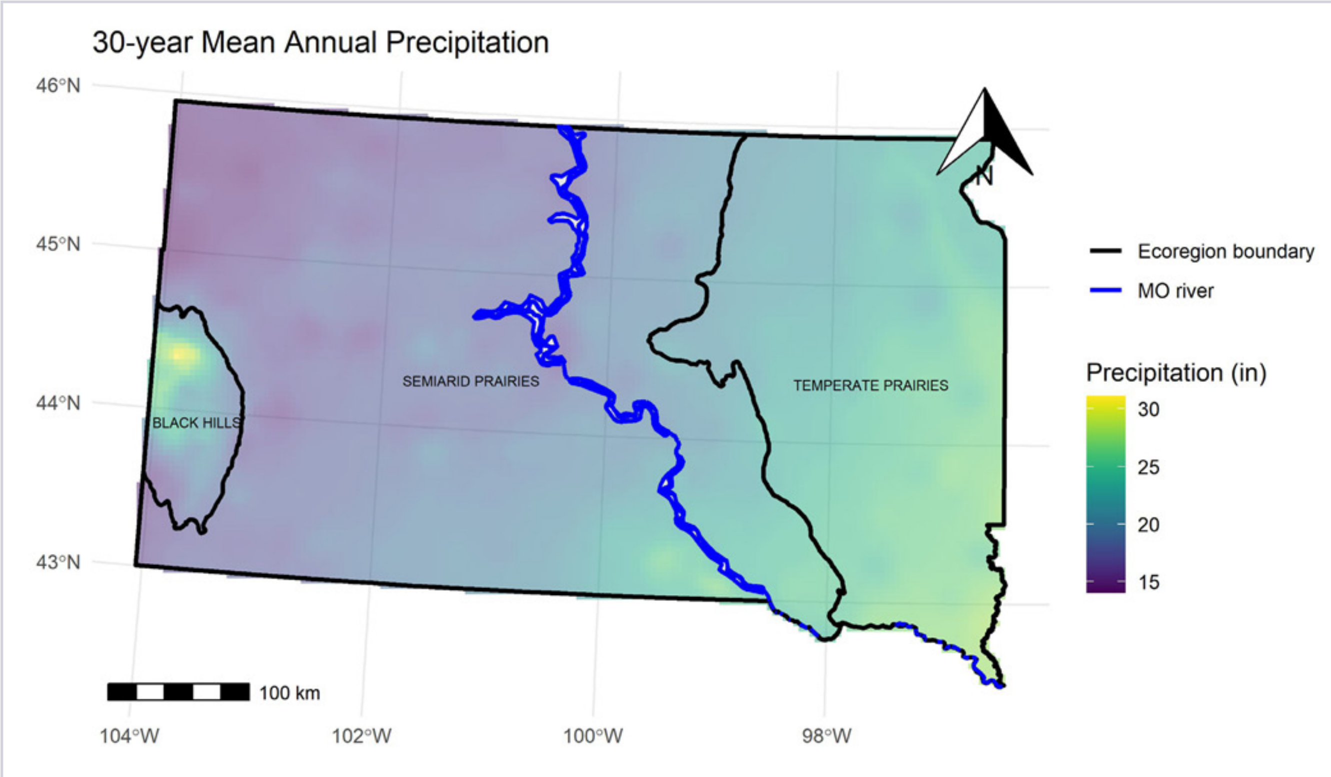


Figure 3—Map of the major eco-regions in South Dakota showing mean annual precipitation (inches). The Missouri River (blue) runs through the center of the State, eco-regions are separated by black lines, and gray outlines depict county borders. Temperate prairies are in the east, semi-arid prairies are in the west, and the Black Hills occurs as an island of ponderosa pine forest in the west. Precipitation is higher in the east and in the Black Hills. Eco-region delineations were based on the EPA II eco-regions (i.e., Black Hills, Semi-arid Prairies, Temperate Prairies). Precipitation values are based on the 30-year normal (1991–2020) of mean annual precipitation (in). PRISM Climate Group, Oregon State University, https://prism.oregonstate.edu. Data created August 3, 2020; Data accessed March 16, 2021. Map created January 6, 2025.

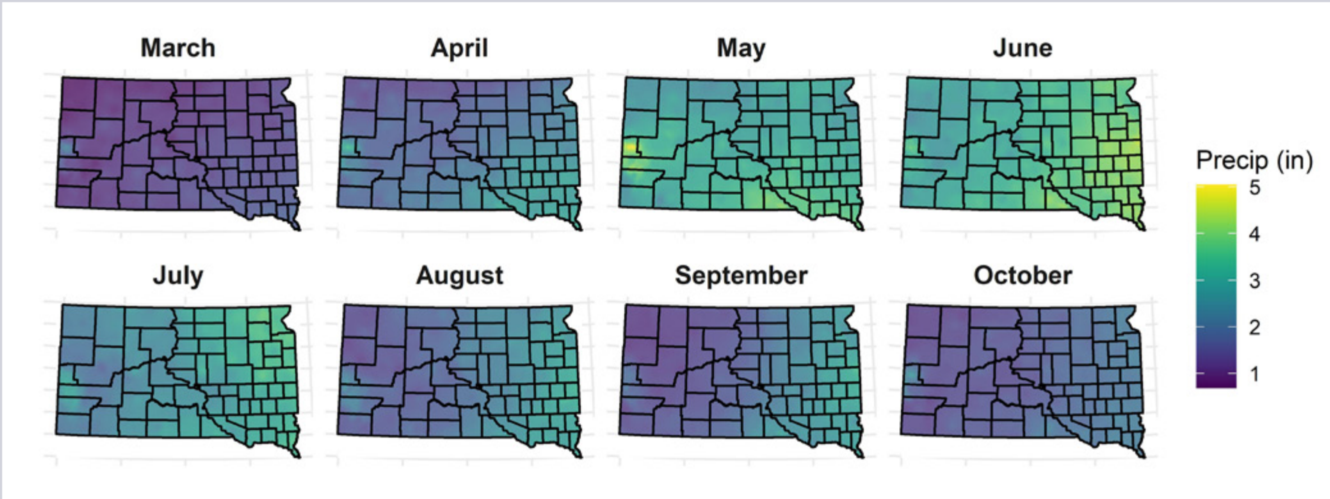


Figure 4—Mean monthly precipitation (in) for South Dakota for the 8 months during the growing season, when approximately 88 percent of annual precipitation occurs. PRISM Climate Group, Oregon State University, https://prism.oregonstate.edu. Map created June 10, 2022.

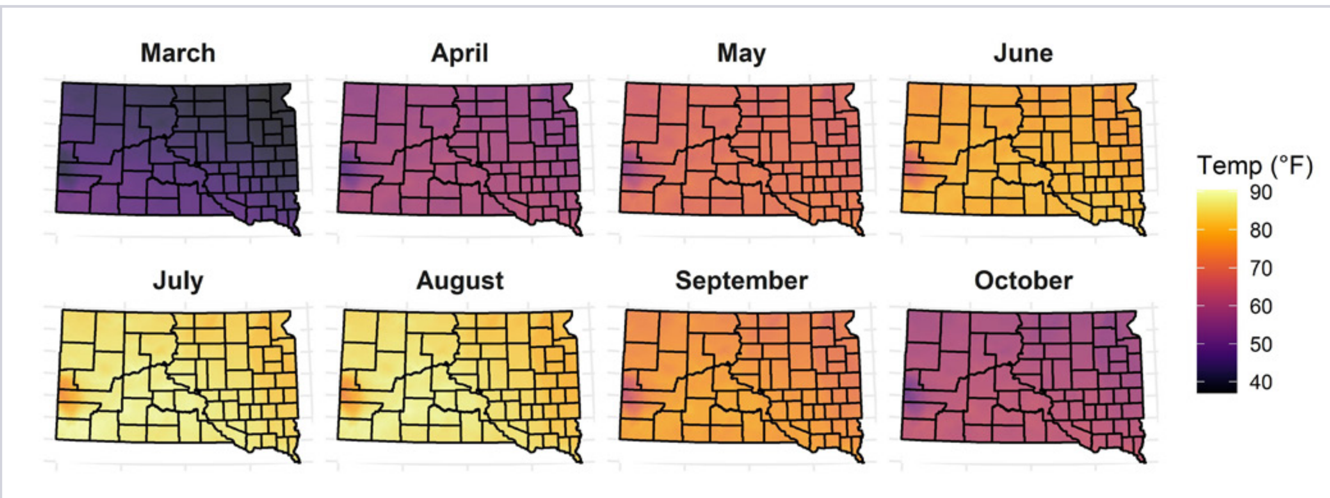


Figure 5—Mean monthly maximum temperature (°F) for the eight primary growing season months in South Dakota. PRISM Climate Group, Oregon State University, https://prism.oregonstate.edu. Map created June 10, 2022.

Original SDDT Model

Source Material for the Model

Because of the strong relationship between water availability and plant growth, precipitation amounts are often used to predict forage production. When making fall stocking decisions in Nebraska and South Dakota, some producers use the precipitation of the previous 2 years to predict how much forage will be available in the coming year (Cole model in Reece et al. 1991). This has worked well in southern grasslands of the United States, as previous and current year annual precipitation can accurately predict current year grass production, explaining 80 percent of its interannual variability (Reichmann et al. 2013). The Cole model proposed weighting, at the end of the growing season (i.e., October), the annual precipitation of the previous year ($p_{t\text{-}1}$) by 75 percent and the annual precipitation of 2 years prior ($p_{t\text{-}2}$) by 25 percent and dividing this value by the historical average annual precipitation ($\bar{p}$),

$$predicted\ percent\ of\ average\ precipitation_t = \frac{0.75 * p_{\text{t-1}} + 0.25 * p_{\text{t-2}}}{\bar{p}} \times 100\%$$

The value produced from this model is a percentage of average precipitation that can be used to estimate how much of the herd should be adjusted for the growing season of the current year (t) (Reece et al. 1991). This is done by multiplying a current stocking rate and the percent of average precipitation. For example:

Long term average precipitation, $\bar{p}$ = 16 in

Year t-2 (Oct–Sep) Precipitation, $p_{t\text{-}2}$ = 12 in

Year t-1 (Oct–Sep) Precipitation, $p_{t\text{-}1}$ = 22 in

Stocking for an average grazing year = 2,700 AUMs (Animal Unit Months)

$$predicted\ percent\ of\ average\ precipitation_t = \frac{0.75 * 22 + 0.25 * 12}{16} \times 100 = 121.9\%$$

Suggested stocking rate for year t = 1.219 x 2,700 = 3,291 AUMs

Note that if the year is t = 2021, then you use the 2019 (*t-2*) and 2020 (*t-1*) precipitation values to predict the stocking rate in 2021. Again, this would only be estimated once a year in October to adjust stocking rates for the coming year. An animal unit month (AUM) is typically the forage amount needed to sustain a 1,000-pound cow with a 6-month-old or younger calf for one month.

This percentage aims to predict the impact of water availability of the previous two seasons on forage production in the upcoming season. The percent of average annual precipitation is roughly equal to the percent of average annual forage production. However, under the assumptions of this model, this prediction will only be accurate if the upcoming season has average precipitation. The model accuracy will be reduced if upcoming seasons have below or above average precipitation. This is not a problem if precipitation is above average precipitation but could be problematic in years of below-average precipitation when forage will be more limited than predicted. It is also important to understand the distribution of rainfall throughout the year. For example, more rain in May as compared to January may have more of a direct effect on forage production, as plants are actively growing in May. Large rainfall events may lead to upper soil saturation and increased runoff, where a large portion of the rainfall does not contribute to increased plant growth. Because of the above reasons, there was a need to develop a more refined model incorporating rainfall timing and amount.

The NRCS sought to create a tool for South Dakota that predicted the percent of average forage production at any time point during the year with the goals of:

1. Reducing the uncertainty of the Cole model,
2. Providing users with near-real-time prediction of drought impacts on forage,
3. Providing users with a model interface where they can enter data using their own local precipitation values, and
4. Providing clear model output to producers to use in drought plans so they can adjust livestock numbers as conditions change and anticipate future conditions to better plan the selling and/or purchasing of livestock.

For more on the development of the SDDT up to 2020, please refer to Supplementary Material S3.

Data sources—

Precipitation data are available from four weather station sources:

1. Applied Climate Information System (98 NOAA NWS COOP stations) https://www.ncei.noaa.gov/products/land-based-station/cooperative-observer-network
2. Community Collaborative Rain, Hail and Snow Network (CoCoRahs, 188 stations) https://www.cocorahs.org/
3. U.S. Department of Agriculture, Forest Service: Remote Automatic Weather Stations (RAWS) from the Desert Research Institute Western Regional Climate Center (25 stations) https://wrcc.dri.edu/wraws/sdF.html
4. The NRCS Snow Telemetry Network (SNOTEL, two stations) https://www.nrcs.usda.gov/resources/data-and-reports/snow-and-water-interactive-map

Users may also select their own automated weather station if it is compatible with the tool and previously configured, or they can enter localized values by hand within the tool.

Missing or unavailable data are inferred using the average of up to six nearby CoCoRahs stations and the historic average from the nearest NOAA NWS COOP station. The CoCoRahs stations have the greatest coverage in the State, and the NOAA NWS COOP stations are the most consistent for long-term data collection. For future predictions, the period of record historic average is used for future months data at that location. A future average or *normal* is assumed. In the SDDT, the user can also adjust for a below-average or above-average future to see best-case and worst-case scenarios, respectively, but for our validation below we assumed average conditions. For example, at the end of March, all data for the previous 2 years through March are known, but April through June data are obtained from the period of record averages to calculate the predicted annual current year precipitation. If there were missing data in the precipitation record, the SDDT filled in a normal value. If the value of precipitation was zero, the SDDT averaged the data from six nearest weather stations to verify that the precipitation total was zero rather than a missing or non-recorded value.

Mathematical summary—

The current SDDT model uses three equations to predict the percent of average forage (i.e., the percent of average precipitation) across the State of South Dakota (fig. 6). The Missouri River runs primarily north and south through central South Dakota, splitting it into western and eastern portions. *West River* refers to the area west of the Missouri River, which is typically drier (<20 in of average rainfall; semi-arid prairie; see fig. 3) than areas east of the river (i.e., *East River*; >20 in of average rainfall; temperate prairie; see fig. 3). Therefore, the models may also be generally referred to as the East River and West River models.

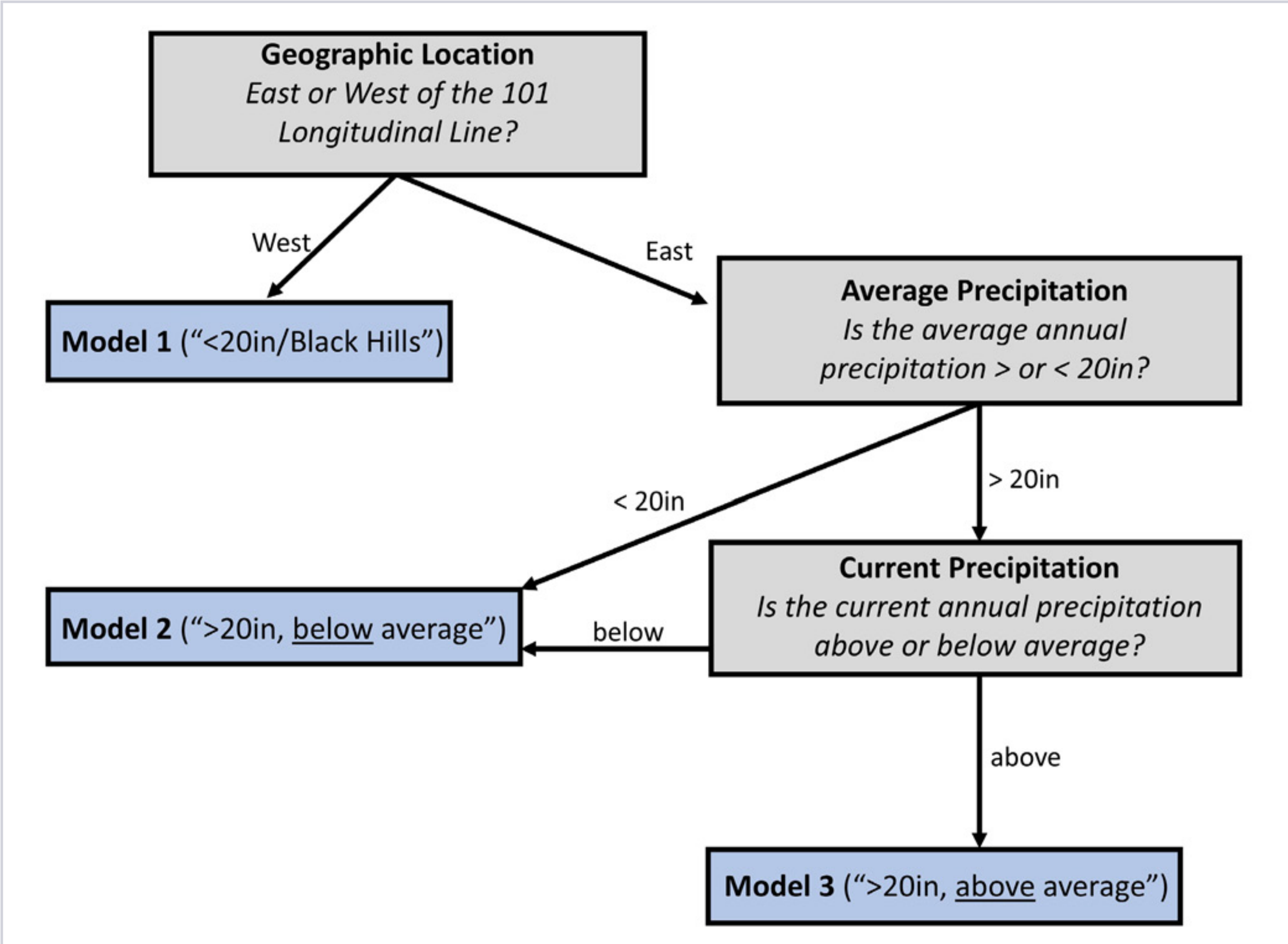


Figure 6—Decision tree for determining which set of model parameters to use for each location.

Model 1 is used for areas with a historical average precipitation of *less* than 20 inches (i.e., "<20 in, Black Hills"). This equation is also used for the Black Hills even though there are locations that may have an average rainfall of more than 20 inches. Model 2 is used for areas with a historical average precipitation of *greater* than 20 inches and current precipitation below the historical average (i.e., ">20 in, *below* average"). Model 3 is used for areas with a historical average precipitation of *greater* than 20 inches and current precipitation above the historical average (i.e., ">20 in, *above* average").

Model predictors include:

- Previous 13–24 months of precipitation from the current date
- Previous 12 months of precipitation from the current date

Model parameters include:

- A threshold for limiting maximum monthly precipitation at 230 percent (Model 1) and 280 percent (Models 2 and 3) of the historical monthly average
- Adjustment for spring precipitation (March–June)
- Adjustment for fall precipitation (September–October)

The SDDT Model—

The current model is composed of three parts: (1) a term describing the precipitation of the 2 previous years, (2) a term describing spring (March–June) precipitation, and (3) a term describing fall (September–October) precipitation. It predicts the percent of normal (y) at site i, in year t, month m, and day d:

$$y_{i,t,m+1,d} = 2yrAvg_{i,t,m} + Spr_{i,t,m,d} + Fall_{i,t,m,d} \tag{1}$$

The 2-year average term (Eqn. 2) weights the previous 12 months percent of normal (Eqns. 3, 5; annual adjusted sum of last 12 months divided by annual historical sum) by 75 percent and weights the percent of normal for the year prior (Eqns. 4, 5; 13–24 months before prediction month) by 25 percent.

$$2yrAvg_{i,t,m} = (1 - \beta_{i,t,m} - \alpha_{i,t,m})\left(0.75\frac{p1'_{i,t,m}}{h'_{i,t,m}} + 0.25\frac{p2'_{i,t,m}}{h'_{i,t,m}}\right) \tag{2}$$

$$p1'_{i,t,m} = \begin{cases} \sum_{m=1}^{m} p^*_{i,t,m} \ , & m = 12 \\ \sum_{m=1}^{m} p^*_{i,t,m} + \sum_{m=m+1}^{12} p^*_{i,t-1,m} \ , & m \neq 12 \end{cases} \tag{3}$$

$$p2'_{i,t,m} = \begin{cases} \sum_{m=1}^{m} p^*_{i,t-1,m} \ , & m = 12 \\ \sum_{m=1}^{m} p^*_{i,t-1,m} + \sum_{m=m+1}^{12} p^*_{i,t-2,m} \ , & m \neq 12 \end{cases} \tag{4}$$

$$h'_{i,t,m} = \begin{cases} \sum_{m=1}^{m} h_{i,t,m} \ , & m = 12 \\ \sum_{m=1}^{m} h_{i,t,m} + \sum_{m=m+1}^{12} h_{i,t-1,m} \ , & m \neq 12 \end{cases} \tag{5}$$

The spring term (Eqn. 6). weights the most recent percent of normal for the spring months of March–June, and the fall term (Eqn. 7) weights the most recent percent of normal for the fall months of September and October.

$$Spr_{i,t,m,d} = \beta_{i,t,m} \begin{cases} \frac{\sum_{m=3}^{6} p^*_{i,t,m}}{\sum_{m=3}^{6} h_{i,t,m}} \ , & m > 6 \\ I_{m \neq 3} \frac{\sum_{m=3}^{m-1} p^*_{i,t,m}}{\sum_{m=3}^{m-1} h_{i,t,m}} + \frac{\sum_{d=1}^{d} p_{i,t,m,d}}{(d/D(m)) h_{i,t-1,m}} \ , & 3 \leq m \leq 6 \\ \frac{\sum_{m=3}^{6} p^*_{i,t-1,m}}{\sum_{m=3}^{6} h_{i,t-1,m}} \ , & m < 3 \end{cases} \tag{6}$$

$$Fall_{i,t,m,d} = \alpha_{i,t,m} \begin{cases} \frac{\sum_{m=9}^{10} p^*_{i,t,m}}{\sum_{m=9}^{10} h_{i,t,m}} \ , & m > 10 \\ I_{m \neq 9} \frac{\sum_{m=9}^{m-1} p^*_{i,t,m}}{\sum_{m=9}^{m-1} h_{i,t,m}} + \frac{\sum_{d=1}^{d} p_{i,t,m,d}}{(d/D(m)) h_{i,t-1,m}} \ , & 9 \leq m \leq 10 \\ \frac{\sum_{m=9}^{10} p^*_{i,t-1,m}}{\sum_{m=9}^{10} h_{i,t-1,m}} \ , & m < 9 \end{cases} \tag{7}$$

Within the model framework, outlying observations are accounted for by adjusting the monthly precipitation to within 230 percent or 280 percent (critical factor, θ) of the historical monthly precipitation (Eqn. 8) depending on the model (table 1). The degree of outlier adjustment (Eqn. 9), as well as the weighting factors on all three components of the model (Eqns. 10, 11), vary by month of prediction and model (i.e., whether the historical annual precipitation is less than, greater than, or equal to 20 inches, and whether the absolute value of the longitude of the weather station is greater than 101°W. If the historical annual precipitation is 20 inches or more, the weighting also depends on whether the previous 12 months of precipitation is greater than the annual precipitation—above-average or below-average year).

$$p^*_{i,t,m} = \begin{cases} p_{i,t,m} \ , & p_{i,t,m} < \theta_{i,t,m} h_{i,t,m} \\ \theta_{i,t,m} h_{i,t,m} \ , & p_{i,t,m} \geq \theta_{i,t,m} h_{i,t,m} \end{cases} \tag{8}$$

$$\theta_{i,t,m} = \begin{cases} w_1 \ , & h'_{i,t,m} < 20 \cup \left|Longitude_i\right| > 101 \\ w_2 \ , & h'_{i,t,m} \geq 20 \cap p1'_{i,t,m} \leq h'_{i,t,m} \\ w_3 \ , & h'_{i,t,m} \geq 20 \cap p1'_{i,t,m} > h'_{i,t,m} \end{cases} \tag{9}$$

$$\beta_{i,t,m} = \left\{ \begin{matrix} b_{1,m} \ , & h'_{i,t,m} < 20 \cup \left|Longitude_i\right| > 101 \\ b_{2,m} \ , & h'_{i,t,m} \geq 20 \cap p1'_{i,t,m} \leq h'_{i,t,m} \\ b_{3,m} \ , & h'_{i,t,m} \geq 20 \cap p1'_{i,t,m} > h'_{i,t,m} \end{matrix} \right\} \tag{10}$$

$$\alpha_{i,t,m} = \left\{ \begin{matrix} a_{1,m} \ , & h'_{i,t,m} < 20 \cup \left|Longitude_i\right| > 101 \\ a_{2,m} \ , & h'_{i,t,m} \geq 20 \cap p1'_{i,t,m} \leq h'_{i,t,m} \\ a_{3,m} \ , & h'_{i,t,m} \geq 20 \cap p1'_{i,t,m} > h'_{i,t,m} \end{matrix} \right\} \tag{11}$$

Table 1—SDDT model term definitions.

Term	Definition
$y_{i,t,\mathrm{m}+1,d}$	Predicted percent of normal production for site *i* n year *t* in month *m* on day *d*
i	Site
m	Month; 1–12
t	Year
d	day; 1, 2,…, *D(m)* where *D(m)* is the maximum number of days in month *m*
$\theta_{i,t,m}$	critical factor for outlier detection at site *i* in month *m* in year *t*
$p_{i,t,m}$	total precipitation for site *i* in month *m* in year *t*
$p^*_{i,t,m}$	adjusted precipitation for site *i* in month *m* in year *t*
$h_{i,t,m}$	historical monthly precipitation for site *i* in month *m* in year *t*
$\beta_{i,t,m}$	weighting factor for spring for site *i* in month *m* in year *t*
$\alpha_{i,t,m}$	weighting factor for fall for site *i* in month *m* in year *t*

Written summary and example—

The SDDT mathematical model can be broken down into a series of steps:

Step 1. Monthly precipitation data for the preceding 24 months are obtained from the nearest weather station to the location of interest, in addition to the monthly historical averages.

Example: We would like to predict the percent of peak forage quantity on May 31, 2015, near Philip, South Dakota. We selected the Philip 2N weather station and obtained its period of record monthly precipitation normals and monthly precipitation data from June 2013 to May 2015 (fig. 7).

Step 2. Monthly precipitation data for the preceding 24 months are adjusted to remove any outliers by placing a precipitation cap on any month that is a certain amount above the historic average for that Month.

Example: Philip, South Dakota is located in the <20 in precipitation zone, which means we will lower any monthly value that is more than 230 percent (2.30 times) greater than the monthly normal value. In this example, October 2013 had 3.87 in of rain when the October monthly historic normal is 1.21 in.

$$\frac{Actual\,Value}{Normal\,Value} = \frac{3.87in}{1.21in} = 3.20$$

October 2013 was 3.2 times the October monthly historic normal precipitation. The maximum October monthly value of precipitation that is allowed is 2.3 times (i.e., 230%) the October normal value, which is

$$Allowable\,percent \text{ x } monthly\,normal = 230\% \text{ x } 1.21\text{in} = 2.78\,\text{in}$$

Therefore, the October 2013 precipitation value that will be used by the model is 2.78 in rather than 3.87 in. This adjustment prevents extreme rainfall events from inflating the percent of peak forage quantity. Each month is checked for this adjustment. In this scenario, December 2013 and August 2014 were also adjusted (fig. 7; Supplementary Material S4).

Step 3. Adjusted monthly precipitation data for the preceding 0–12 and 13–24 months are each summed and divided by the historic annual precipitation for the same time span. The 0–12-month time period is then weighted by 75 percent and the 13–24-month time period is weighed by 25 percent. These two values are summed to create a rough percent of normal annual precipitation. Note that we are interested in peak production, which is assumed to occur on July 1 each year in the Northern Great Plains.

Example: The previous 0–12-month period up to July 1, 2015, is July 2014 to June 2015. On May 31, 2015, we do not know the precipitation of June 2015. Therefore, we will assume that it will be the long-term June monthly normal of 3.19 in. Therefore, the sum of adjusted precipitation for 0–12 months prior to July 1, 2015, is 16.88 in. The previous 13–24 months period up to July 1, 2015, is July 2013 to June 2014. Using the adjusted precipitation from step 2, the sum of precipitation for the 13–24 months prior to June 1, 2015, is 16.43 in (fig. 8A). The annual precipitation normal for Philip, South Dakota, is 15.67 in.

$$percent\,of\,normal = \frac{Adjusted\,Actual\,Precipitation}{Annual\,Precipitation\,Normal} \text{ x } 100\%$$

$$percent\,of\,normal\,for\,previous\,12\,months = \frac{16.88in}{15.67in} \text{ x } 100\% = 107.72\%$$

$$percent\,of\,normal\,for\,previous\,13\,to\,24\,months = \frac{16.43in}{15.67in} \text{ x } 100\% = 104.85\%$$

Because the most recent precipitation is assumed to have a greater effect on current year forage (see correlation of semi-arid grasslands in Colorado in Sala et al. 2012), the previous 12 months are weighted by 0.75 (i.e., 75%) and the previous 13–24 months are weighted by 0.25 (i.e., 25%).

$$Weighted\,12\,month\,term = 107.72\% \text{ x } 0.75 = 80.79\%$$

$$Weighted\,24\,month\,term = 104.85\% \text{ x } 0.25 = 26.21\%$$

These weighted values are summed together to provide the first term of the model, which is also a rough estimate of the percentage of average forage quantity.

$$Seasonally\,unadjusted\,percentage\,of\,average\,forage\,quantity =$$
$$Weighted\,12\,month\,term + Weighted\,24\,month\,term =$$
$$80.79\% + 26.21\% = 107.00\%$$

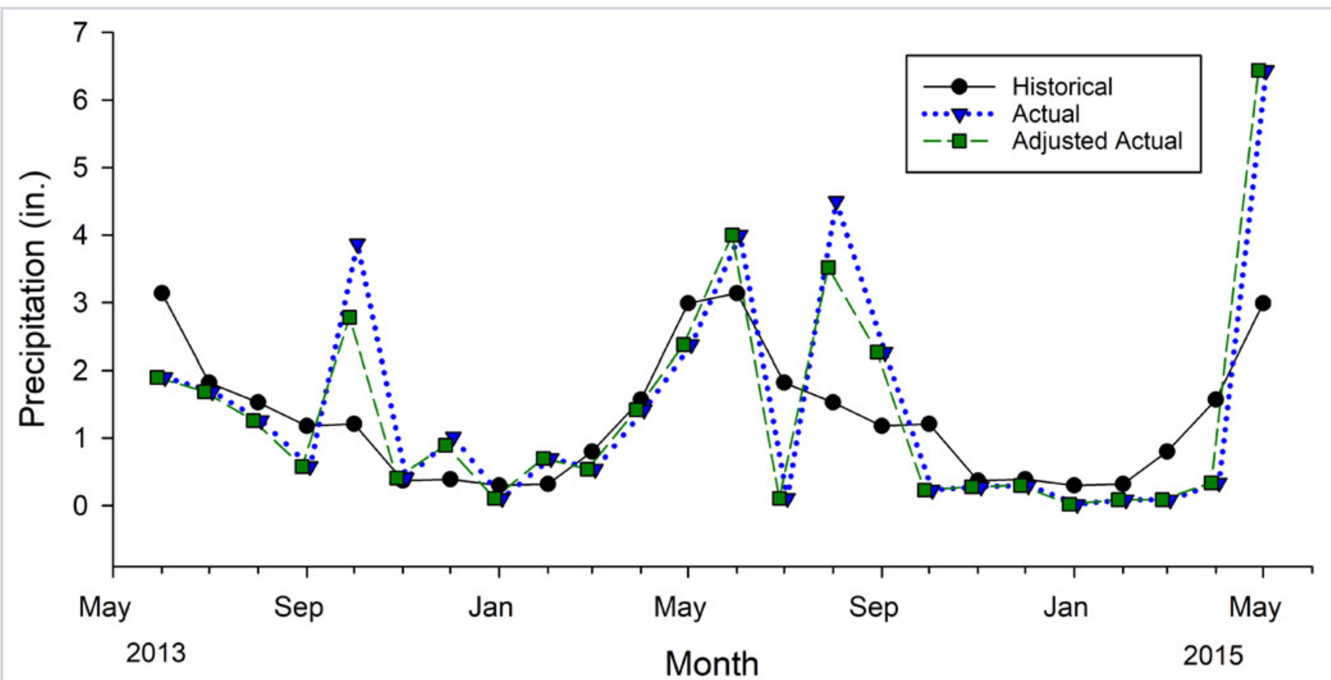


Figure 7—Demonstration of the Precipitation Critical Thresholds in the SDDT model: historical monthly period of record precipitation normals, 2013–2015 actual precipitation, and 2013–2015 adjusted precipitation for Philip, South Dakota. Precipitation records were obtained from the Philip 2N NOAA NWS weather station. Monthly values that were greater than 230 percent of the monthly normal value were adjusted to values of 230 percent of the monthly normal value. This data is available in Supplementary Material S4.

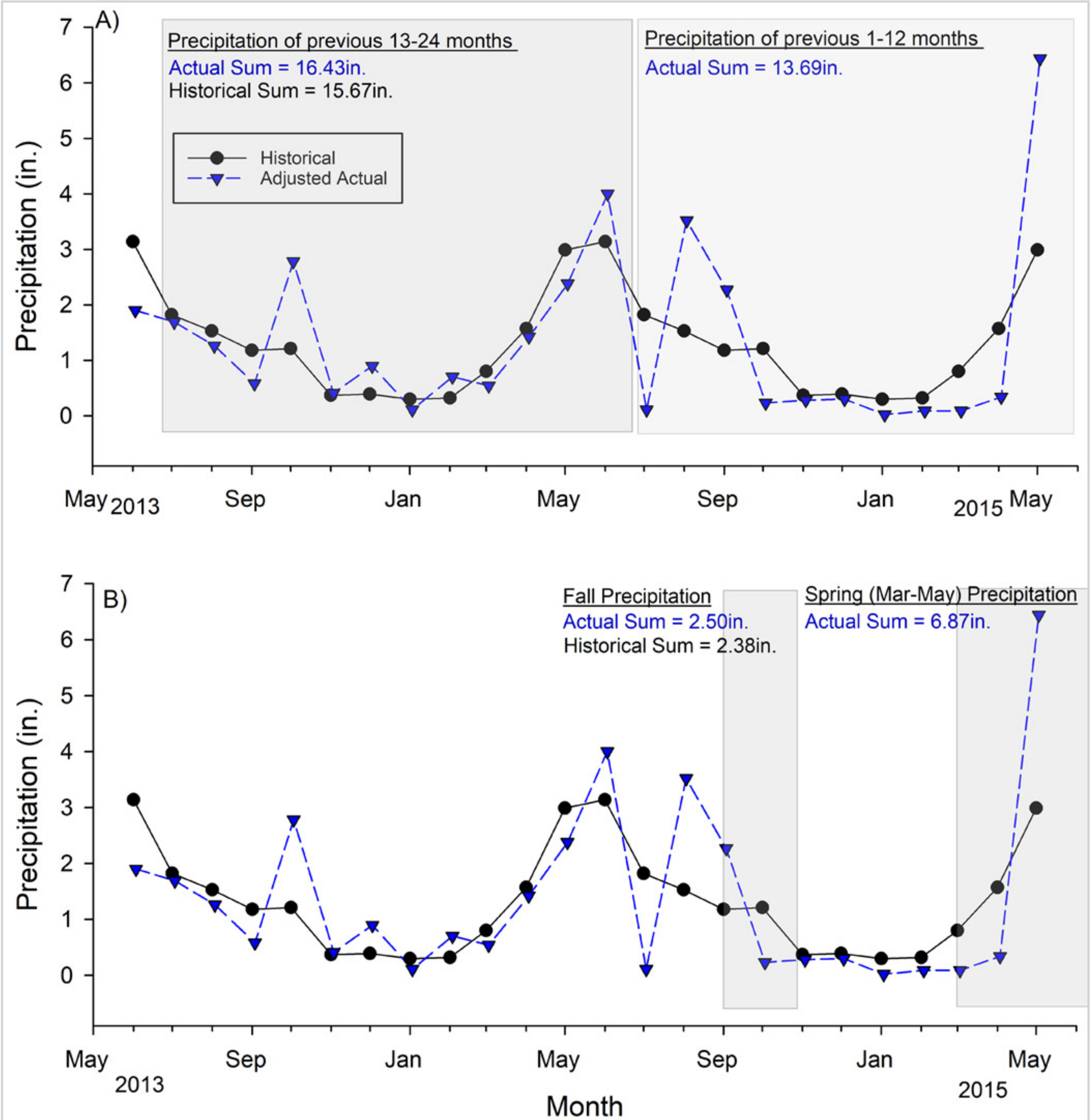


Figure 8—Example of the precipitation sources used in the SDDT model for estimating percent of peak forage production for 2015 on May 31, 2015. (A) Monthly precipitation normals and 2013–2015 adjusted precipitation for Philip, South Dakota, showing the previous 12 month and 13–24-month precipitation time periods. The first term of the model considers the contributions of annual precipitation 1 and 2 years before the year of interest. (B) Seasonal fall and spring precipitation time periods used in the second and third model terms. The most recent fall precipitation (September–October) and spring precipitation (March–June) periods to the date of inquiry (May 31, 2015, in this example) are used. The June 2015 precipitation is unknown, so the total actual sum of the spring precipitation will require use of the historical average precipitation for June.

Step 4. Adjusted monthly precipitation data for the preceding spring period (Mar–Jun) and fall period (Sep–Oct) are each summed and divided by the historic normal data for the same time span. In the current model, spring and fall precipitation are weighted differently among the three models (<20 in average rainfall, >20 in average annual rainfall with current year below average, and >20 in average annual rainfall with current year above average). Together, these factors are added to the first model term to create a seasonally adjusted percentage of normal forage production value.

Example: Precipitation concentrated in peak growing periods (spring and fall) can have a great effect on forage production. To take this into account, precipitation from the previous spring and fall are evaluated and factored into the model using the second and third terms.

Because we are evaluating the percent of peak forage production for 2015 on May 31, 2015, the most recent spring precipitation period is from March through June 2015 and the most recent fall precipitation period is from September to October 2014 (fig. 8B). Because we do not know what the June 2015 precipitation will be, we use the period of record normal June precipitation from the Philip 2N weather station to estimate the June 2015 precipitation, which is 3.19 in.

Using the adjusted precipitation from step 2, the sum of spring precipitation is 10.06 in (this includes the estimated June 2015 precipitation and observed March through May 2015 precipitation), and the normal for this period is 8.56 in (fig. 8). The sum of fall precipitation is 2.50 in, and the normal for this period is 2.38 in (fig. 8).

$$percent\,of\,normal = \frac{Adjusted\,Actual\,Precipitation}{Precipitation\,Normal} \text{ x } 100\%$$

$$percent\,of\,normal\,for\,spring\,precipitation = \frac{10.06in}{8.55\,in} \text{ x } 100\% = 117.66\%$$

$$percent\,of\,normal\,for\,fall\,precipitation = \frac{2.50in}{2.39\,in} \text{ x } 100\% = 104.6\%$$

Because Philip is in western South Dakota, where annual rainfall is less than 20 in, we will use the model 1 weights (fig. 6) where the spring precipitation is weighted by 0.15 and the fall precipitation is weighted by 0.1875 (table 2).

$$Weighted\,spring\,precipitation\,term = 117.66\% \text{ x } 0.15 = 17.65\%$$

$$Weighted\,fall\,precipitation\,term = 104.6\% \text{ x } 0.1875 = 19.61\%$$

Table 2—Original and newly optimized model parameter values.

Parameters	Original <20 in	Optimized <20 in	Original >20 in, below	Optimized >20 in, below	Original >20 in, above	Optimized >20 in, above
Critical threshold	2.3	2.42	2.3	4.54	2.8	1.79
Spring weight	0.15	0.26	0.2	0.39	0.5	0.44
Fall weight	0.1875	0.16	0	0	0.15	0.26

These weighted values are summed together with the adjusted first term of the model to calculate the percent of average forage production. The seasonally unadjusted first term of the model weights the first term so that together the fall, spring, and first term weights sum to one. Therefore, the weight of the first term would be:

$$1 - spring\,weight\; - fall\,weight = 1 - 0.15 - 0.1875 = 0.6625$$

$$percentage\,of\,average\,forage\,production =$$
$$adjusted\,first\,term + spring\,adjustment + fall\,adjustment =$$
$$(107.00\% \text{ x } 0.6625) + 17.65\% + 19.61\% = 108.15\%$$

Model output and use—

The SDDT output provides predicted peak forage production estimates in the form of percent of average forage production. If an estimate is above 100 percent, peak forage production estimates are expected to be greater than average production levels. If an estimate is below 100 percent peak forage production estimates are expected to be less than average production levels. Predictions for the percent of normal production can be made daily and are based on the most up-to-date precipitation information available for the area of prediction. The model is currently in a Microsoft Excel© file[1] that is accessible for all users. It provides a way for users to enter their own data and create a drought plan based on the model output for their location if they choose (NRCS South Dakota 2020).

In addition to providing point estimates (i.e., individual site estimates), the NRCS also creates Statewide condition maps. To create these maps, model calculations are made for each weather station, and then their values are interpolated across a map of South Dakota using the Inverse Distance Weighting (IDW) interpolation method in ArcGIS©. Areas of South Dakota that are at values of less than 93 percent are color-coded green, 85–93 percent are yellow, and less than 85 percent are red indicating drought concerns (fig. 9). These maps are updated monthly throughout the year on the South Dakota NRCS website[1].

1 https://www.nrcs.usda.gov/conservation-by-state/south-dakota/range-pasture

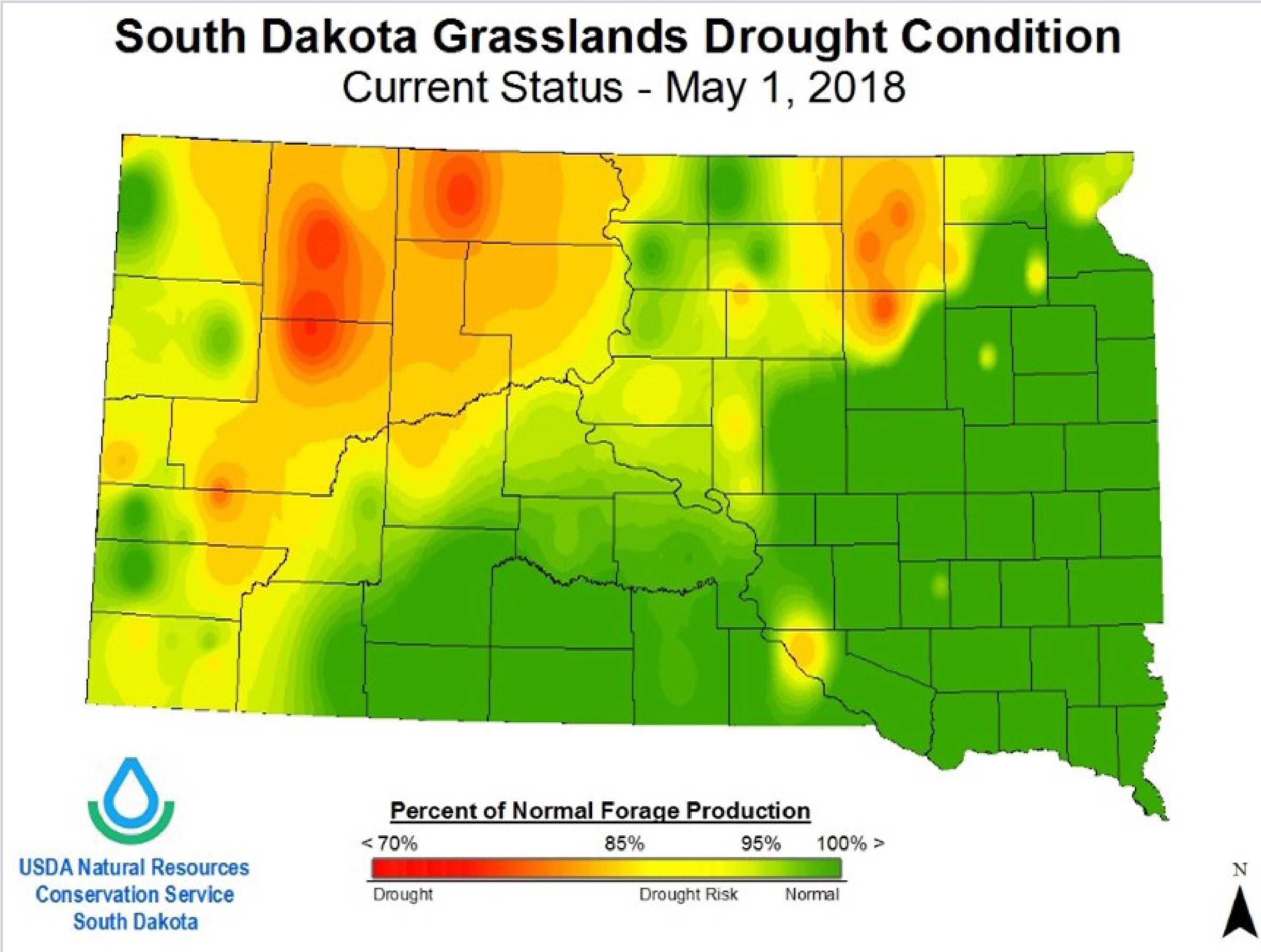


Figure 9—Example of Statewide condition map produced on May 1, 2018.

There are several examples of agencies and producers using output from the SDDT. Currently, the South Dakota Game, Fish and Parks, Division of Wildlife, uses the SDDT to refine their elk contingency tag numbers in the Black Hills area. Contingency tags are issued to help reach target population numbers in various portions of the Black Hills. If the population estimates result in contingency tags being issued, the number is further refined based on vegetation production predictions determined by the SDDT. South Dakota livestock producers use the SDDT to plan for future conditions in the late fall and winter. Beginning in November, the SDDT predicts the next year's peak production number. For example, if the SDDT shows below-average peak production in the upcoming grazing season, a producer may choose to purchase fewer replacement heifers or may reduce the number of yearlings or stockers that they would purchase in the early to mid-winter. As spring approaches, predictions from the SDDT can inform the producer on livestock culling levels if forage production shortfalls appear to be looming.

SDDT Validation

Objectives

After completing our first objective to formally describe the current SDDT model, we (the authors) had three overarching objectives in validating the current model:

1. Confirm the best model fit of the SDDT precipitation model for peak forage predictions.
2. Evaluate how well the model estimates July peak forage starting the previous November through July on a monthly basis using National Resources Inventory data (i.e., evaluate the uncertainty around the peak forage predictions).
3. Evaluate the best model fit of the SDDT precipitation model for monthly forage predictions (i.e., evaluate how well the tool predicts percent of forage production in near-real time).

These objectives are accomplished using NRI data and Representative Values (RV) of forage production from Ecological Site Descriptions to predict the percentage of average forage production. These production values will be compared with model predictions based on precipitation data. Analyses included both overall SDDT model fit for the State and evaluation of how well the three sub-models fit the NRI data. Our aim was to assess the current model variables and weights of each variable. For future model improvements, model assumptions may be tested using variable selection.

Methods

Validation data—

As part of a larger national effort, the NRI has collected clipped biomass data every year from approximately 150 locations (i.e., primary sampling units) across South Dakota since 2003 (NRCS CSSM 2022). Primary sampling units (PSUs) are randomly chosen each year. A PSU east of the Missouri River is 40 acres, whereas a PSU west of the river is 640 acres (i.e., one section of land) due to heterogeneity in irrigated land and homogeneity in forest, range, and barren land in the west according to the NRI protocol.

Five, 1.92 ft^2 quadrats of herbaceous vegetation are clipped and separated out by species at each PSU (fig. 10). These quadrats are averaged for each site. Because sampling occurs at any time during the growing season and across private and public land with multiple types of management, sample areas may have experienced grazing and be at different seasonal growth stages. To adjust for these differences, the NRI protocol corrects for grazing by providing an estimate of percentage grazed for the sample and corrects for growth stage by evaluating at what time point along the growth curve the sample was collected.

Growth curves are provided in the individual Ecological Site Descriptions (ESDs) and are adjusted using vegetation clipping data collected for the purpose of developing accurate growth curves (Sedivec et al. 2007, 2009). Additionally, the NRI samples are weighed in the field and the weight includes the moisture content at the time of clipping (i.e., green weight). The sample or subsample of each species is then allowed to air dry and is weighed until the value stabilizes. The stabilized air-dry value is divided by the green weight value to determine a percent dry weight correction factor. Oven-dried weights are not used in the NRI data. If a comparison is desired, air-dry samples typically weigh 112 percent compared to oven-dried samples as they still retain about 12 percent moisture (Emily Helms Rohrer, Natural Resources Conservation Service, Rapid City, SD, personal communication, November 14, 2020). After correcting for all these factors, an NRI estimate of dry forage amount—assuming no grazing at peak production in July—is produced. We also used the NRI estimates of production at the time of collection (i.e., without the seasonal correction factor applied) to validate how well the drought tool performs in real time. Samples from a total of 1,650 NRI PSUs between 2003 and 2016 were used for the validation.

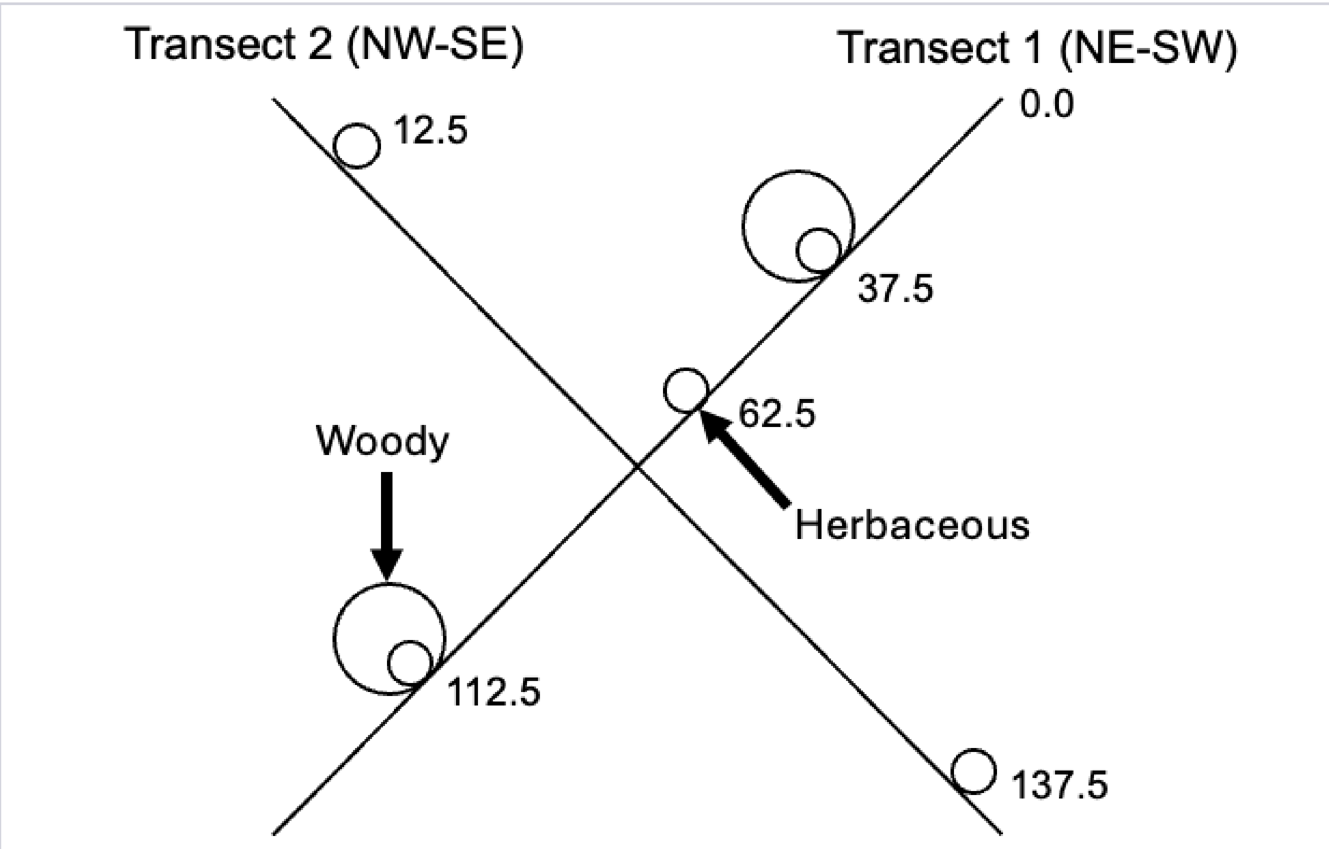


Figure 10—National Resources Inventory Sampling Primary Sampling Unit (NRI PSU). Herbaceous quadrats (small circles) are located at five set locations along the transects at each PSU (number values are in ft). Usually, all five quadrats are sampled, but occasionally, one or two points are left out due to the quadrat falling on a *non-site* (e.g., standing water, rock outcrop, etc.).

To increase coverage in the Black Hills, an additional 27 sampling units collected by the Forest Service and the NRCS were added to the validation data set. These sampling units primarily were taken at three locations (Robinson Flats, French Creek, and Castle Creek) between 2005 and 2020. These data were collected in a manner like that of the NRI data.

To obtain equivalent values between the NRI data and the percent of normal production produced by the SDDT model, predicted percentages were multiplied by the expected production value (representative value) of the Ecological Site Description (ESD) of the PSU point. For the real-time predictions, we accounted for seasonality using the ESD reference values adjusted by their monthly growth curves. The optimal community representative value (RV) was taken from the ecological site at the center point of the PSU microplot (where the two transects intersect; see fig. 10).

Each ESD has a range of expected annual production. For example, the Clayey 13–16 in Precipitation Zone (PZ) Reference State Community 1.1 has an average production value (also known as a representative value) of 1,800 lbs per acre; low production is considered 900 lbs per acre and high production is 2,500 lbs per acre. If NRI data were outside of the ESD's range of production, the site was no longer in a reference state community. For example, the site could be heavily invaded by perennial cool-season grasses that alter its productivity outside normal bounds. In these cases, we removed these datapoints from the dataset because we could not gauge what their representative value should be. For example, NRI datapoints in the Clayey 13–16 in. PZ Reference State Community 1.1 that were below 900 and above 2,500 lbs/acre were not used in the analysis. In total, there were 1,677 datapoints in the dataset. We removed 375 points that were outside the bounds of their ESD Reference State production range and 251 points with missing data, which left 1,051 points to analyze (805 for Model 1, 122 for Model 2, and 124 for Model 3). Missing data could be a result of precipitation data with zeros, missing clipping data, or a missing representative value.

To obtain SDDT production estimates for each PSU, the SDDT was calculated for the nearest weather station to each NRI PSU to estimate peak production for the year each PSU was collected. For the first validation objective, SDDT peak production estimates used precipitation data through July 1 of the year in consideration. For the second objective, SDDT peak production estimates were made using precipitation data from the last day of November of the prior year through July of the year of prediction. For the third objective, precipitation data up to the day of collection were used for SDDT production estimates.

Optimization methods—

We optimized the parameters of the SDDT model, which included the model-based spring and fall weighting factors and the precipitation critical (threshold) values. The three models were based on average historical precipitation greater than or less than 20 in and longitude. For peak production estimates (Objective 1), this consisted of nine total parameters (single spring and fall weighting factors) and for real-time production estimates (Objective 3) a total of 75 parameters (spring and fall weighting factors varying by month). Because the original model is not a simple linear regression, we used optimization techniques to determine appropriate critical values and weighting factor values. All analyses were conducted using the statistical software package R (R Core Team 2020).

Optimization was carried out using the *optim* function with the method of Byrd et al. (1995) from the optimx package (Nash 2014; Nash and Varadhan 2011) so that lower and upper bounds could be set on the parameters, and differentiation of the objective function was not necessary (method='L-BFGS-B' in the *optim* function in R). We set the lower bound of the critical value to 1 with an upper bound of 10 to ensure the algorithm kept the original intent of using this parameter for outlier detection. This way, any single, oddly high precipitation value did not overly influence the prediction. Spring and fall weighting factors were set to have a lower bound close to zero (0.0001) and an upper bound of 1 to maintain the intended weighting structure. We used the sum of squared error, $SSE = \sum_1^n \left(y_i - \hat{y}_i\right)^2$, where y_i is the clipping production value for observation i, and $\hat{y}_i$ is the predicted percent production multiplied by the reference production value, as our objective function to minimize.

Visualizing uncertainty—

To evaluate the predictive uncertainty of the drought tool, we calculated residual differences on both scales (pounds and percent) by taking the observed value and subtracting the predicted value from the optimized model value. We reported estimates of uncertainty by the average absolute residual error (difference between predicted and observed values) as well as with an approximate margin of error. The approximate margin of error assumed a symmetric interval around our point estimates and is calculated by multiplying the standard deviations of the residual differences by 2 (two). We then examined the distribution of these errors and present several summary statistics.

Results and Discussion

Validation Objective 1: Optimization of model thresholds and spring and fall weighting factors for peak prediction—

Overall model—

Model optimization using the original model variables did not greatly improve the original SDDT v7.6 estimates (fig. 11). The "greater than 20 in below" model saw the greatest improvement (i.e., blue dots closer to the red 1:1 line than the black dots in fig. 11). This indicates that the original SDDT model was already estimating the percentage of peak forage production as well as a model using annual and seasonal precipitation factors could. Optimization reduced the overall sum of square error (SSE) by just 6 percent with an average absolute residual error of 18 percent (406 lbs). Thus, assuming a symmetric interval, the approximate uncertainty for peak prediction is +/-48 percent (or 1,079 lbs, double the standard deviations of error, which were 24 percent or 540 lbs). Therefore, seasonal weighting and critical factors did not shift greatly between the original SDDT model and the newly optimized SDDT model (table 2).

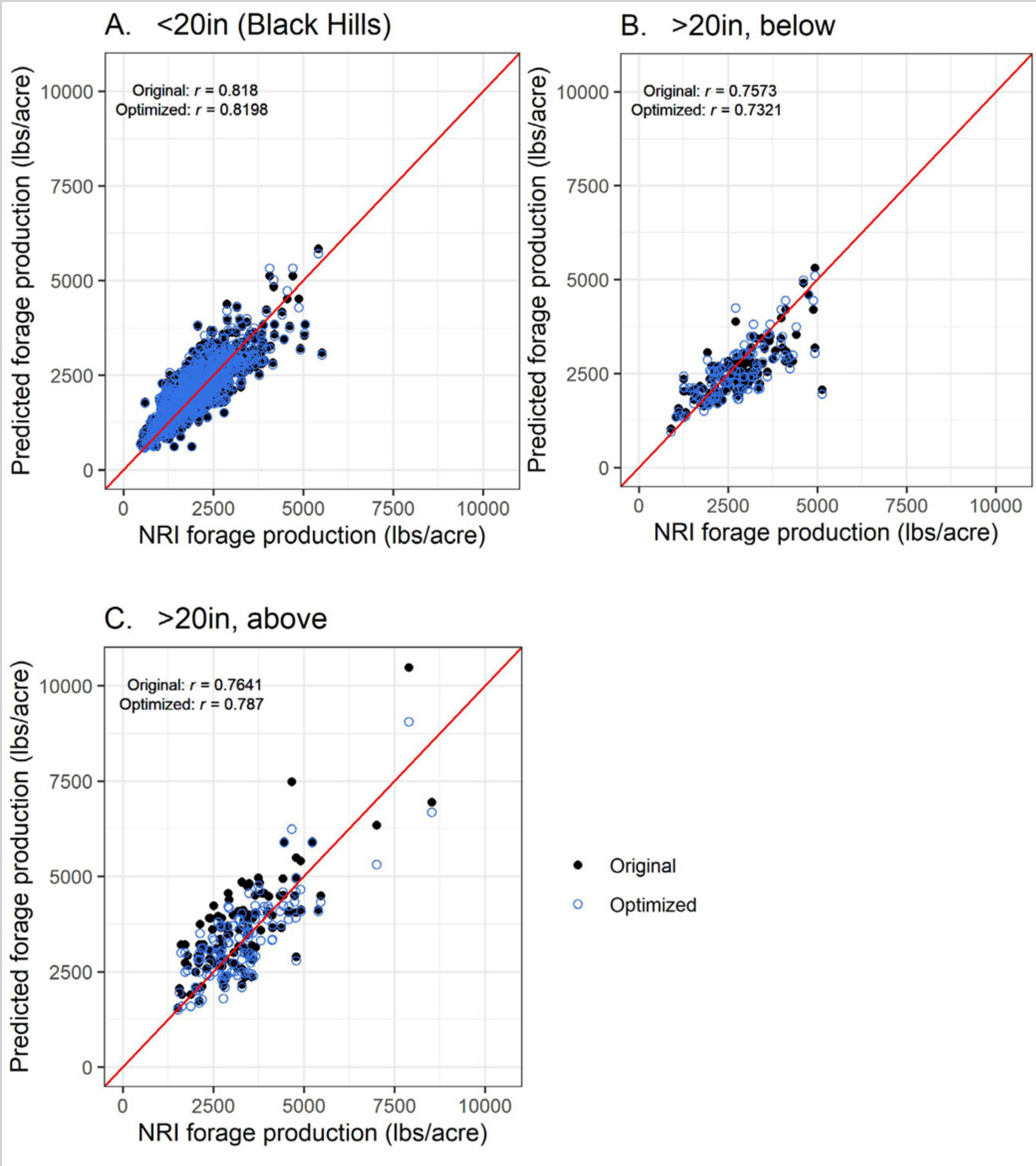


Figure 11—The SDDT forage prediction correlation to actual forage production for original and optimized SDDT models estimating peak prediction. The solid (black) and open (blue) dots are the original and optimized model predictions, respectively. The red diagonal line is the 1:1 line. This figure shows the actual forage production estimated from the NRI clipping data on the x-axis and the SDDT percent of normal estimate multiplied by the ESD representative value on the y-axis.

The optimization improved the estimates for loamy ecological sites (fig. 12). Loamy soil sites are prevalent across South Dakota, comprising about 24.5 percent of all sampled NRI sites and 39.6 percent of all mapped soils across the State. The model had the most difficulty optimizing for sub-irrigated ecological sites, likely due to their difference in soil water movement. The original and optimized SDDT models tended to underpredict high production clayey sites (fig. 12). The year in which forage data were collected did not substantially influence the optimization model (fig. 13). Therefore, the original and optimized models were estimating similar forage amounts in years with and without drought, and NRI observers from different years were not greatly influencing the model optimization.

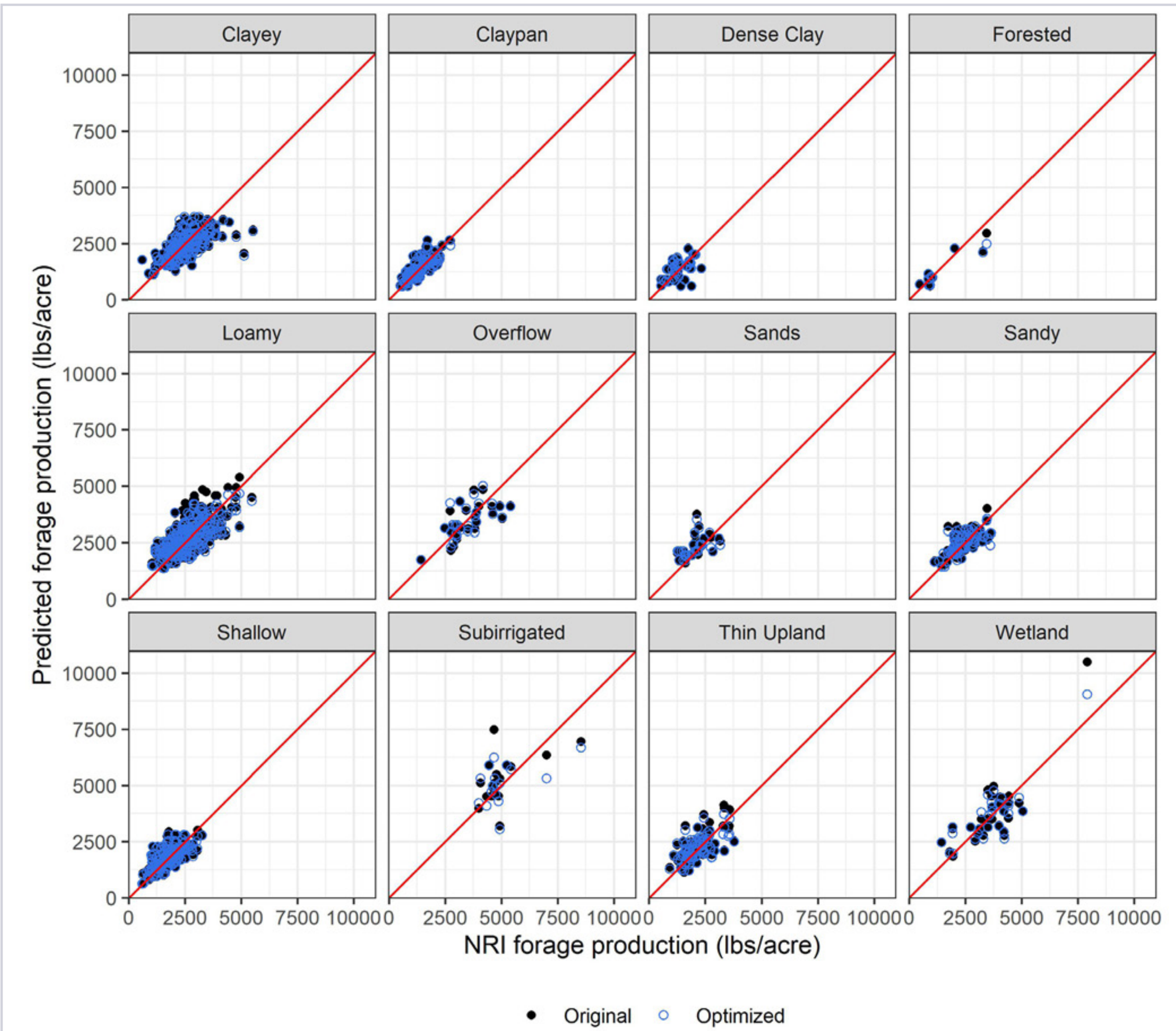


Figure 12—The SDDT forage prediction correlation to actual forage production for the original and optimized SDDT models for 12 Ecological Site Descriptions (ESDs). The solid (black) and open (blue) dots are the original and optimized model predictions, respectively. The red diagonal line is the 1:1 line. This figure shows the actual forage production on the x-axis and the SDDT percent of normal estimate multiplied by the ESD representative value on the y-axis. Representative values of the ESDs used in this study are found in Supplementary Material S5.

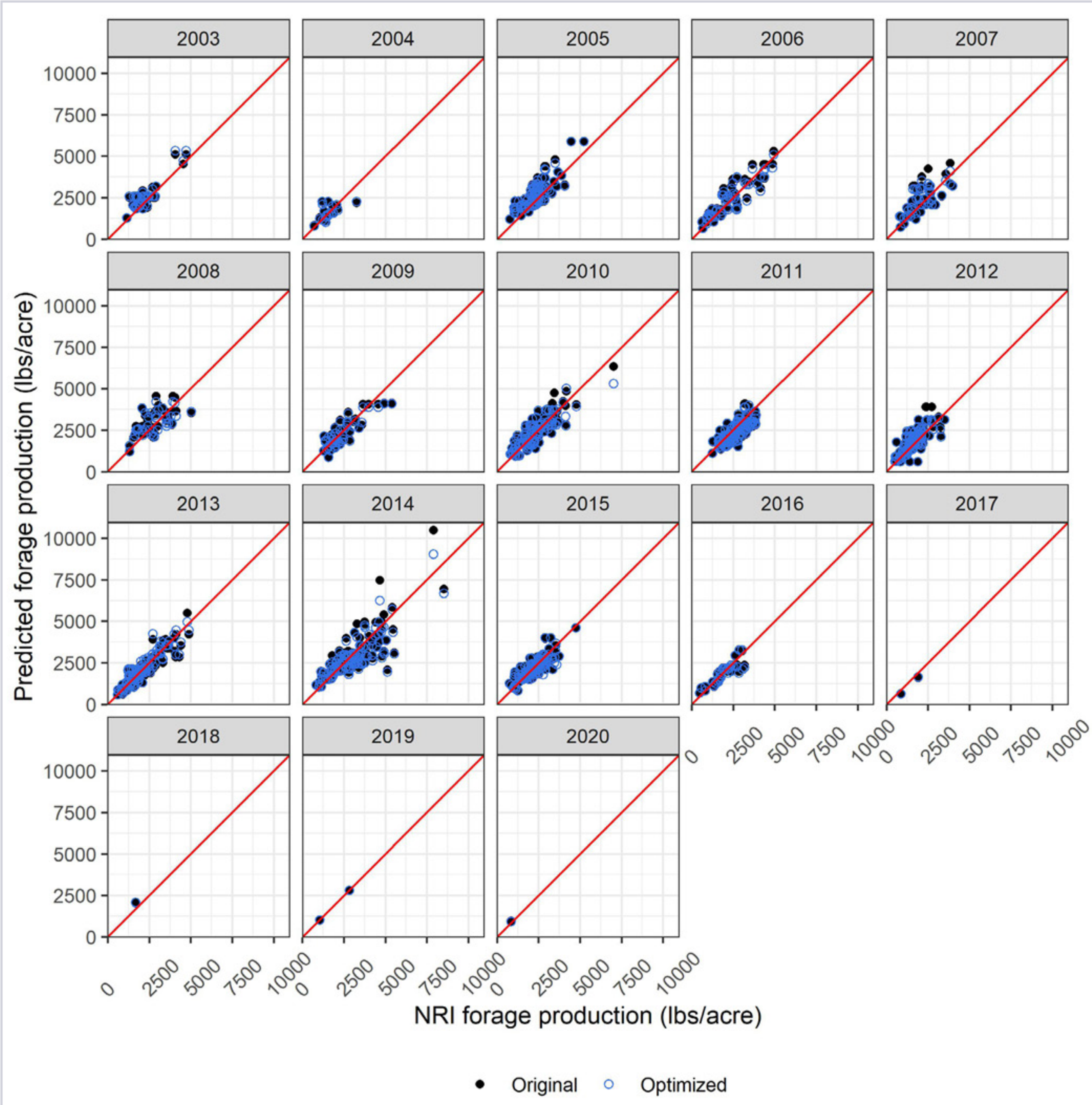


Figure 13—The SDDT forage prediction compared to actual forage production for original and optimized SDDT models subset by Ecological Site Description (ESD) type. The solid (black) and open (blue) dots are the original and optimized model predictions, respectively. The red diagonal line is the 1:1 line. Note that the more recent years contain data from the Black Hills (2017–2020) only. This figure shows the actual forage production on the x-axis and the SDDT percent of normal estimate multiplied by the ESD representative value on the y-axis.

Although the error size (lbs/acre) increased as the Representative Values increased, the percent error did not vary across Representative Values, indicating that error was not biased by the Representative Value (fig. 14). As the Black Hills area is of special interest to managers of wildlife, particularly elk, the 9 percent of datapoints from the Black Hills were extracted from the larger optimization effort to examine how the optimization affected forage estimates for the Black Hills. The error value for the Black Hills did not differ greatly from the value outside of the Black Hills and had a smaller range of values likely due to its smaller sample size (fig. 15).

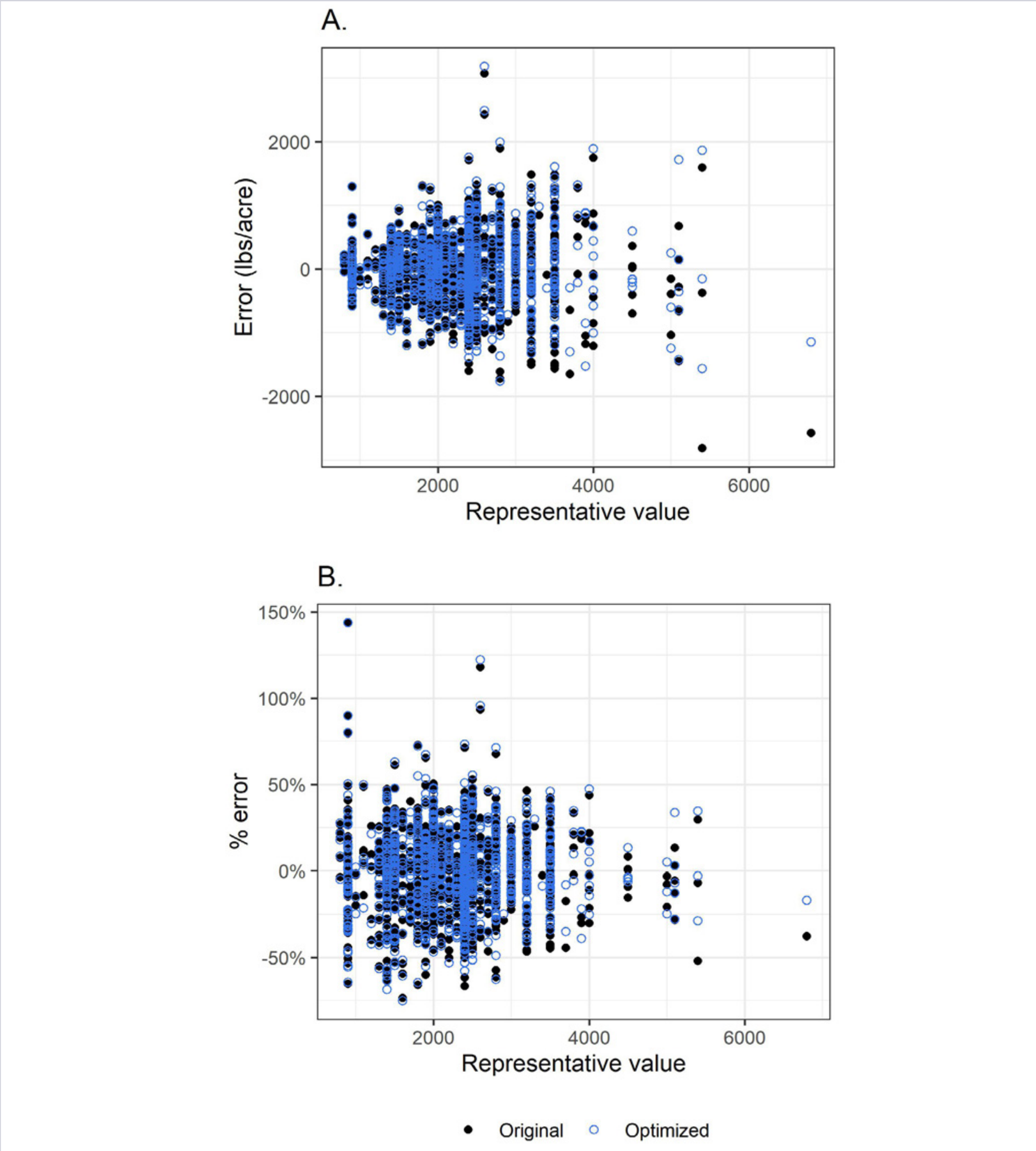


Figure 14—Residual error (observed-predicted) in lbs (A) and percent error (B) of original (black symbols) and optimized (blue symbols) models across representative values.

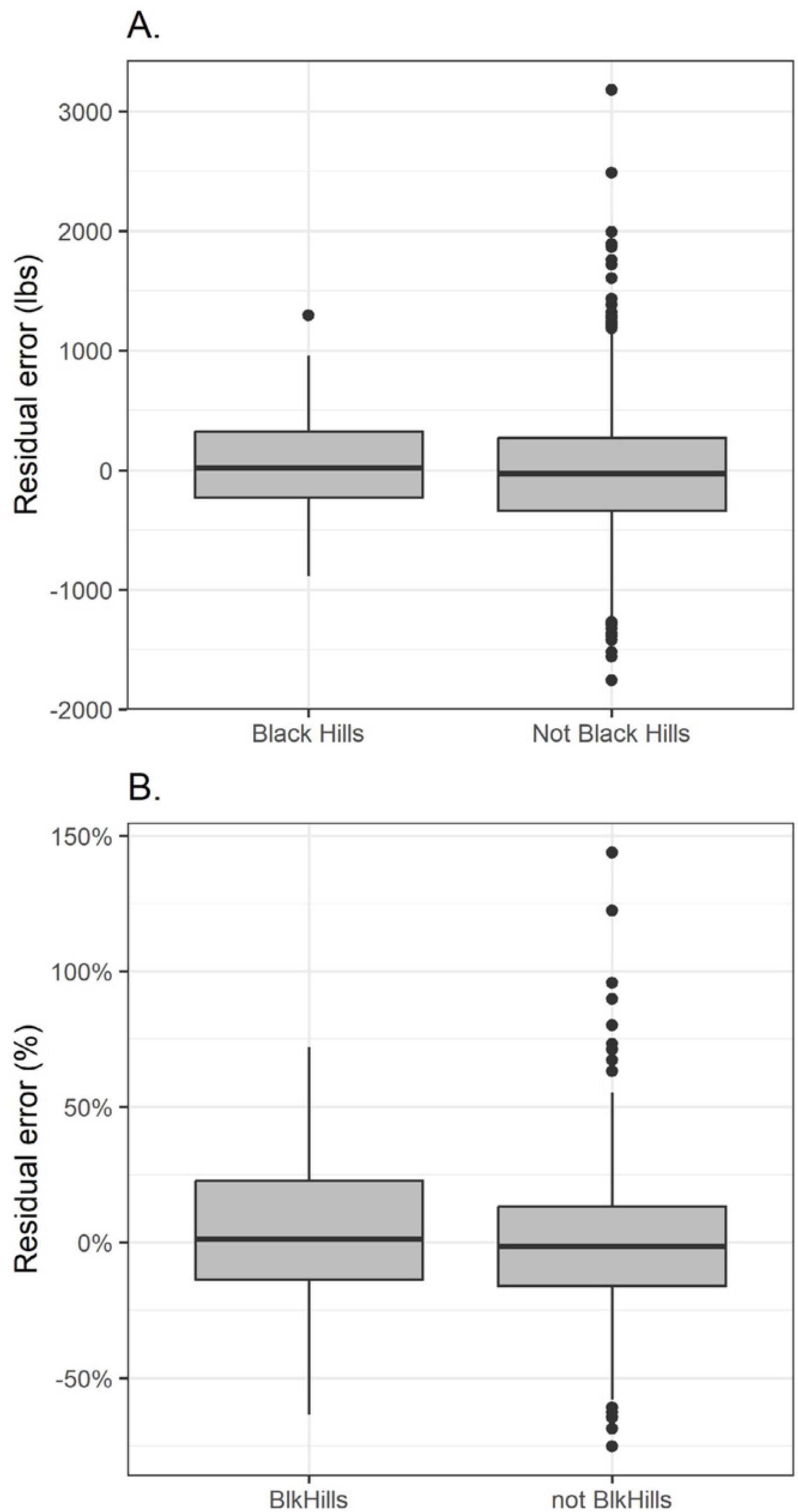


Figure 15—Residual (A) and percent (B) error (observed-predicted) for datapoints located within the Black Hills region and outside the Black Hills region. Boxes represent interquartile range (IQR) with solid black line representing the median and solid black whiskers extending to Q1-1.5*IQR and Q3+1.5*IQR. Outliers existing beyond the whiskers are shown by black points.

Residual error varied spatially across South Dakota (fig. 16). Certain areas of the State have better weather station coverage than others, which may lead to more uncertainty in model predictions. Areas where COOP weather stations have stopped collecting data in recent years may create high uncertainty in their estimates.

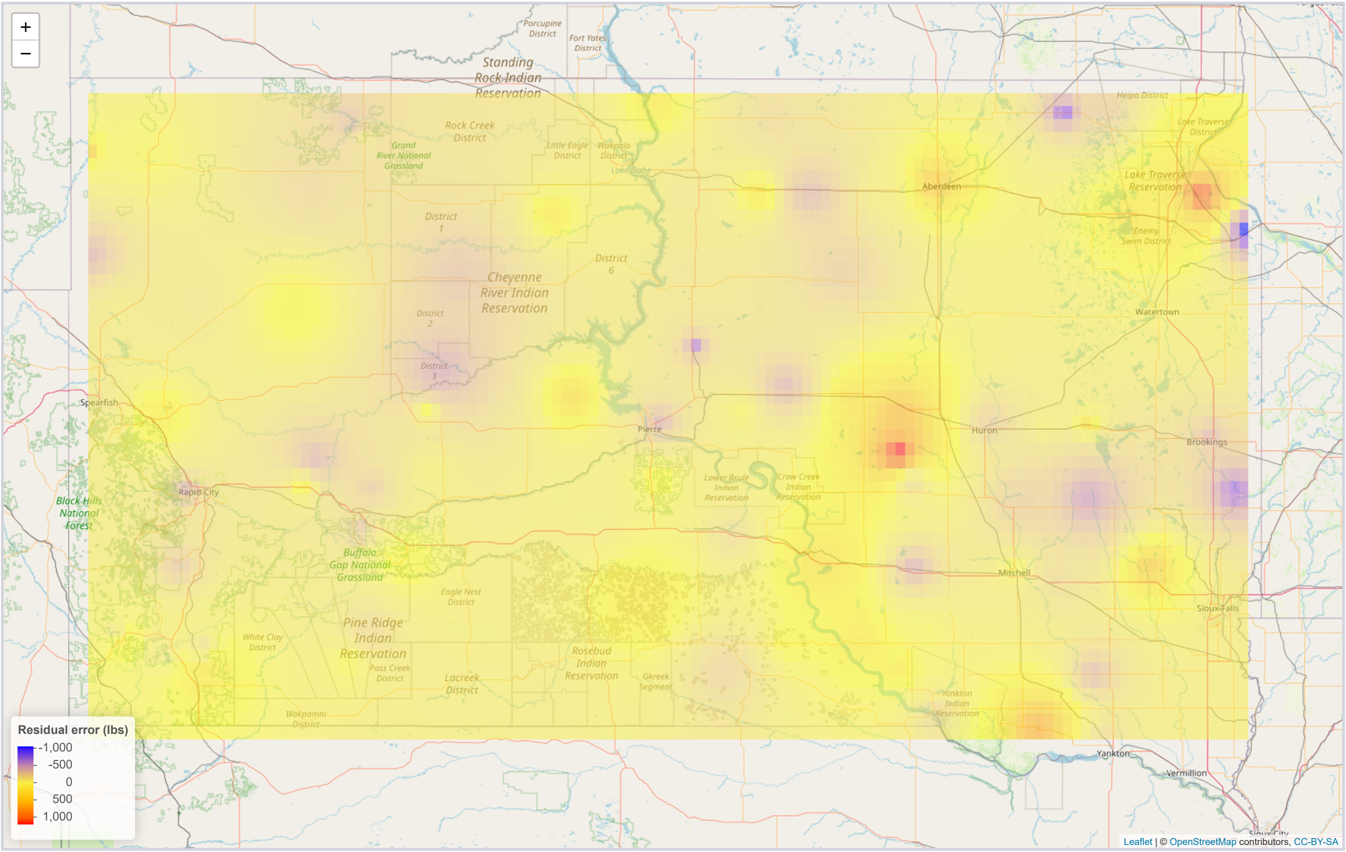


Figure 16—Residual error (observed-predicted; in lbs) across the State.

Validation Objective 2: Evaluation of time to peak forage estimates—

Optimization reduced the overall sum of squared error $SSE = \sum_{i=1}^{n}(observed_i - predicted_i)^2$ for estimated peak forage production in the 7 months leading up to peak production by 3 percent, with an average absolute residual error ($|observed_i - predicted_i|$) of 19 percent (423 lbs). Thus, assuming a symmetric interval, prediction uncertainty was ± 49 percent (1,093 lbs). When considering the regional submodels, the >20 in below model tended to consistently underpredict forage production as compared to the <20 in model and the >20 in above model (fig. 16). The >20 in above model saw the greatest improvement from the optimization (fig. 17).

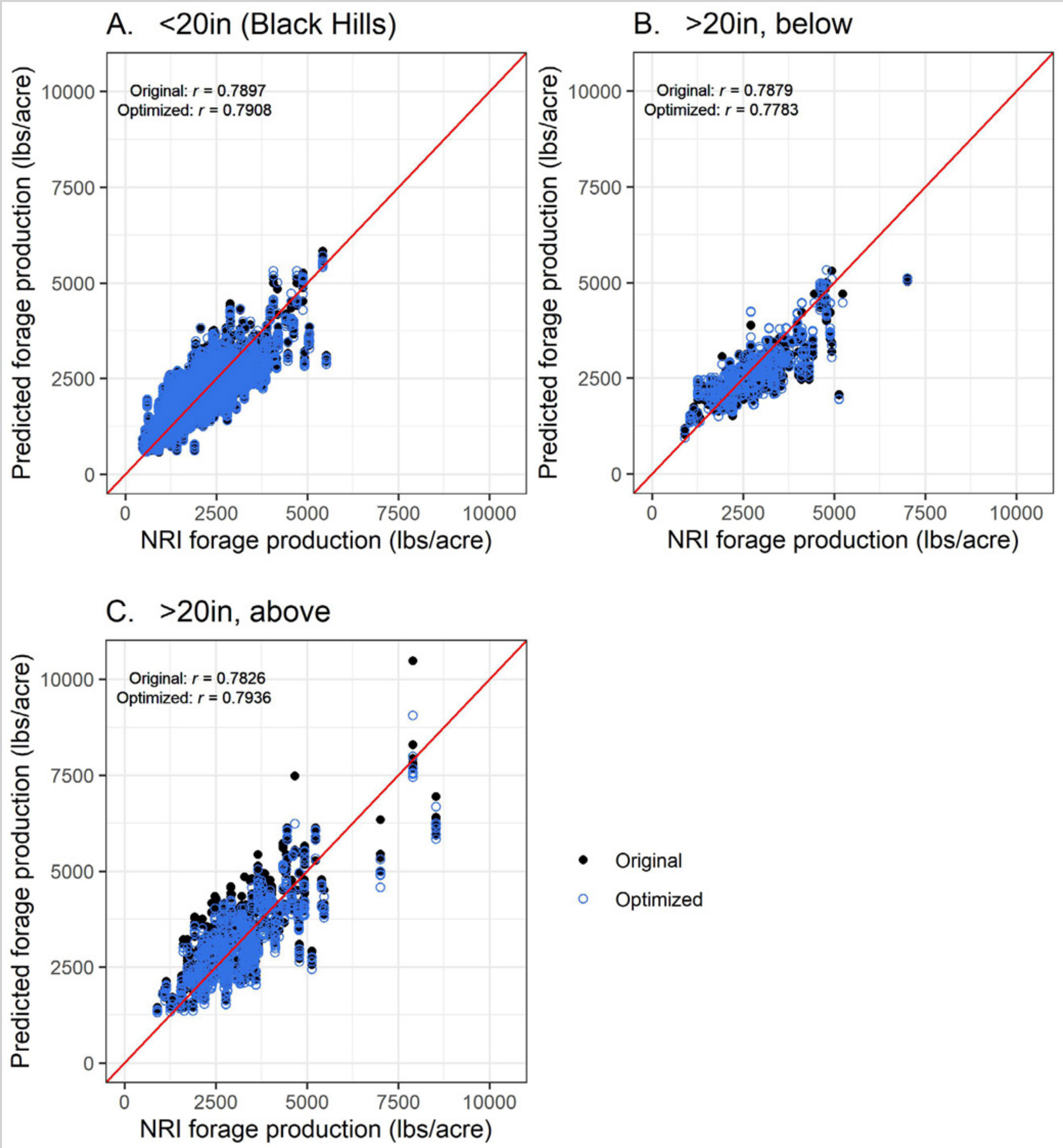


Figure 17—For each model (fig. 6), the SDDT forage prediction correlation to actual forage production for original and optimized SDDT models estimating peak prediction results from each month (November through July) leading up to peak forage production. The solid (black) and open (blue) dots are the original and optimized model predictions, respectively. The red diagonal line is the 1:1 line. Actual forage production estimated from the NRI clipping data is on the x-axis and the SDDT percent of normal estimate multiplied by the ESD representative value is on the y-axis.

The SDDT prediction timing did not have a large effect on model error as evidenced by the model error being similar across months (fig. 18). Therefore, prediction error was not reduced as precipitation information was added throughout the winter and subsequent growing seasons. Overall, the SDDT tended to slightly underpredict in the months leading up to the time of peak production (November through May), while the average error approached zero (i.e., greater precision) the closer to the time of the peak when the prediction was made. However, differences across months were very minor in the overall model.

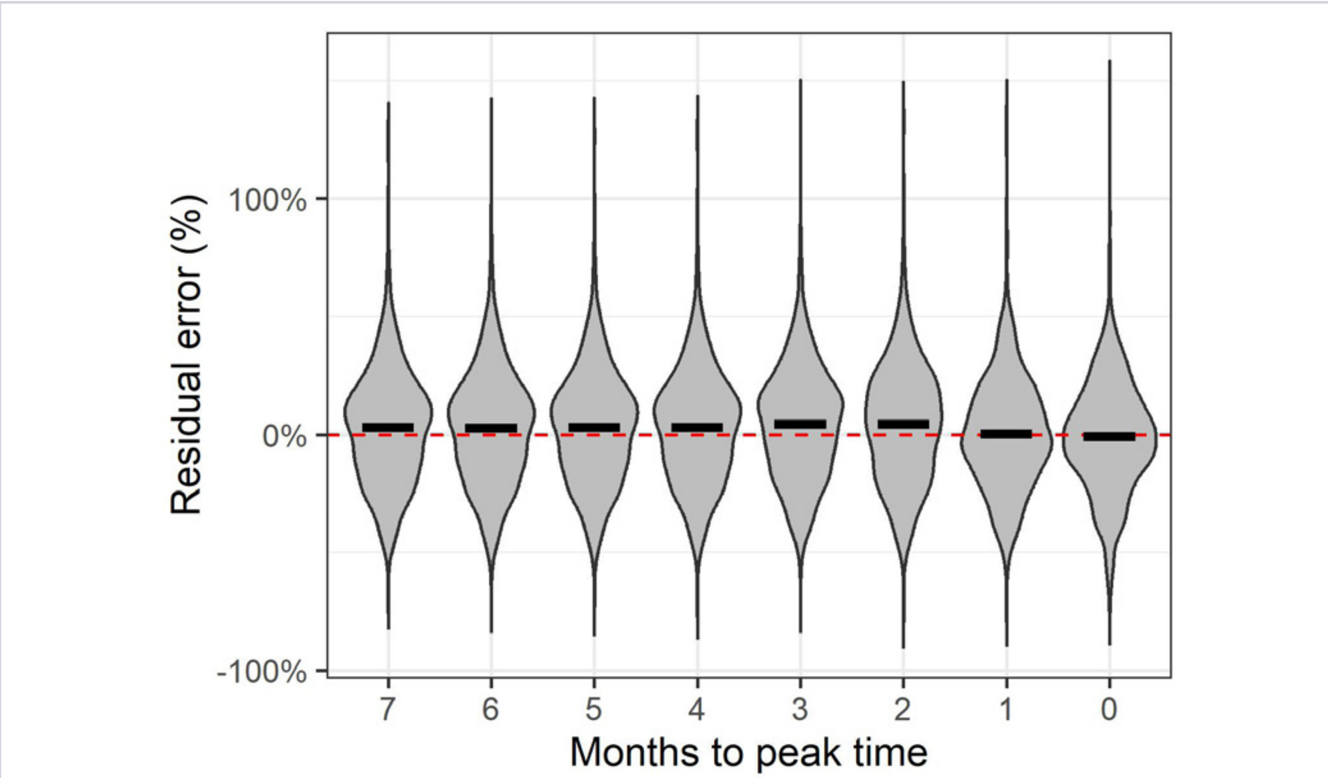


Figure 18—Distributions of residual error (observed-predicted) of optimized SDDT in months leading up to time of peak prediction, where the number 7 on the x-axis represents the error in November (i.e., 7 months prior to the year of peak prediction) and the zero (0) on the x-axis represents the error at the time of peak prediction (July 1). The dashed red horizontal line represents zero error, and the short black bars represent monthly mean error.

Substantial uncertainty exists due to multiple sources of error (see *Results and Discussion* section below) so that in some cases the prediction improved the closer to the peak time the prediction was made (fig 19, left panel). In other cases, there did not appear to be a pattern of increased precision when the prediction was made closer to peak time of forage production (fig. 19, right panel). The degree of uncertainty is also demonstrated in figure 18, where the error distribution appears to be greater—but more precise on average—a few months before peak time as compared to the predictions made in the fall before peak time. Approximately 75 percent of all observations were within 25 percent of the NRI forage estimates in all months leading up to peak time, as compared to an increase in the proportion of observations that were within 5–10 percent of the NRI estimates as the peak time became closer (fig. 20).

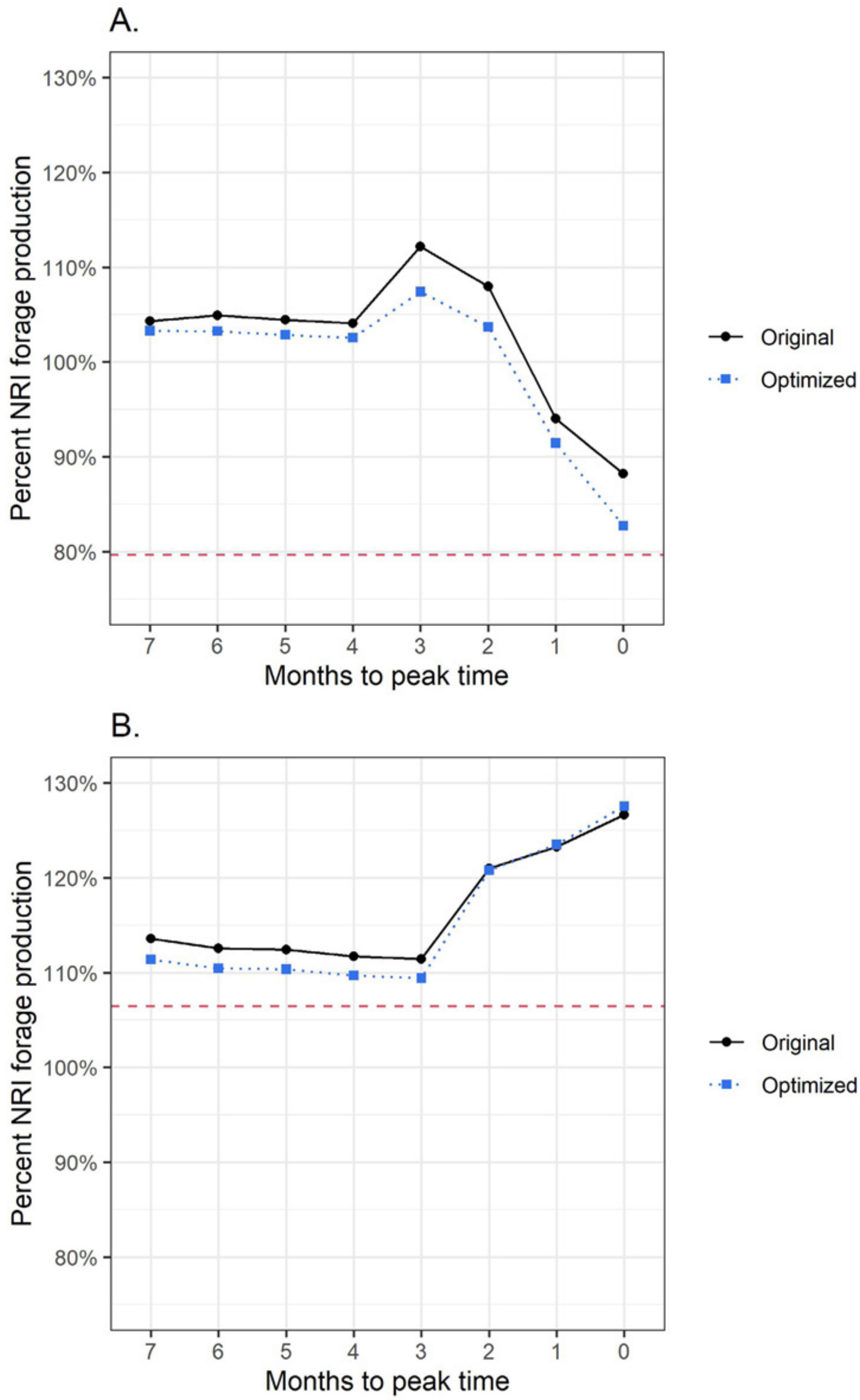


Figure 19—Predicted percent of forage production (y-axis) in the months leading up to peak time (x-axis) for two clipping points. (Left: clipping point example no. 1. Right: clipping point example no. 2). The black line represents the original SDDT predictions, the blue line represents the optimized SDDT prediction, and the red dashed line shows the actual percent forage production estimated from the NRI clipping data. Both points show improvement from the optimization. However, the error pattern is not consistent for all points, demonstrating that individual sampling locations may be responding to different sources of error.

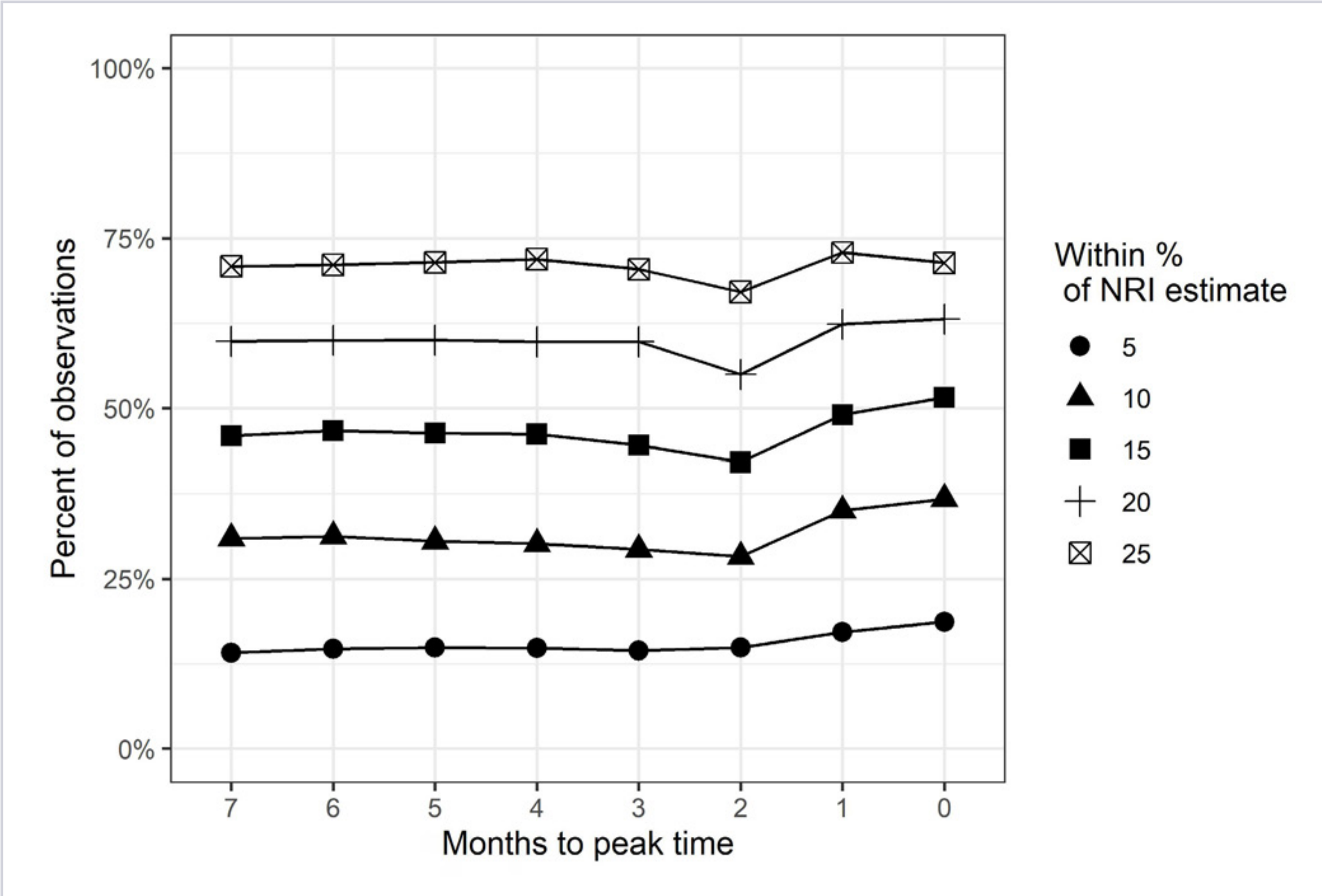


Figure 20—Percent of SDDT predictions that are within 5–25 percent of the NRI estimates in the months leading up to the peak time.

Validation Objective 3: Optimization of real-time predictions—

The optimization of the real-time predictions for the SDDT showed the most improvement with an overall reduction in square sum of error (SSE) of 56 percent (Supplementary Material S6 contains model weighting factors). However, the error was slightly higher with these real-time predictions with an average absolute residual error of 22 percent (382 lbs) and a margin of error of 59 percent (1,002 lbs). The optimization improved the *<20 in, Black Hills* model the most, reducing some outlier predictions that were severely overpredicting forage amounts (fig. 21).

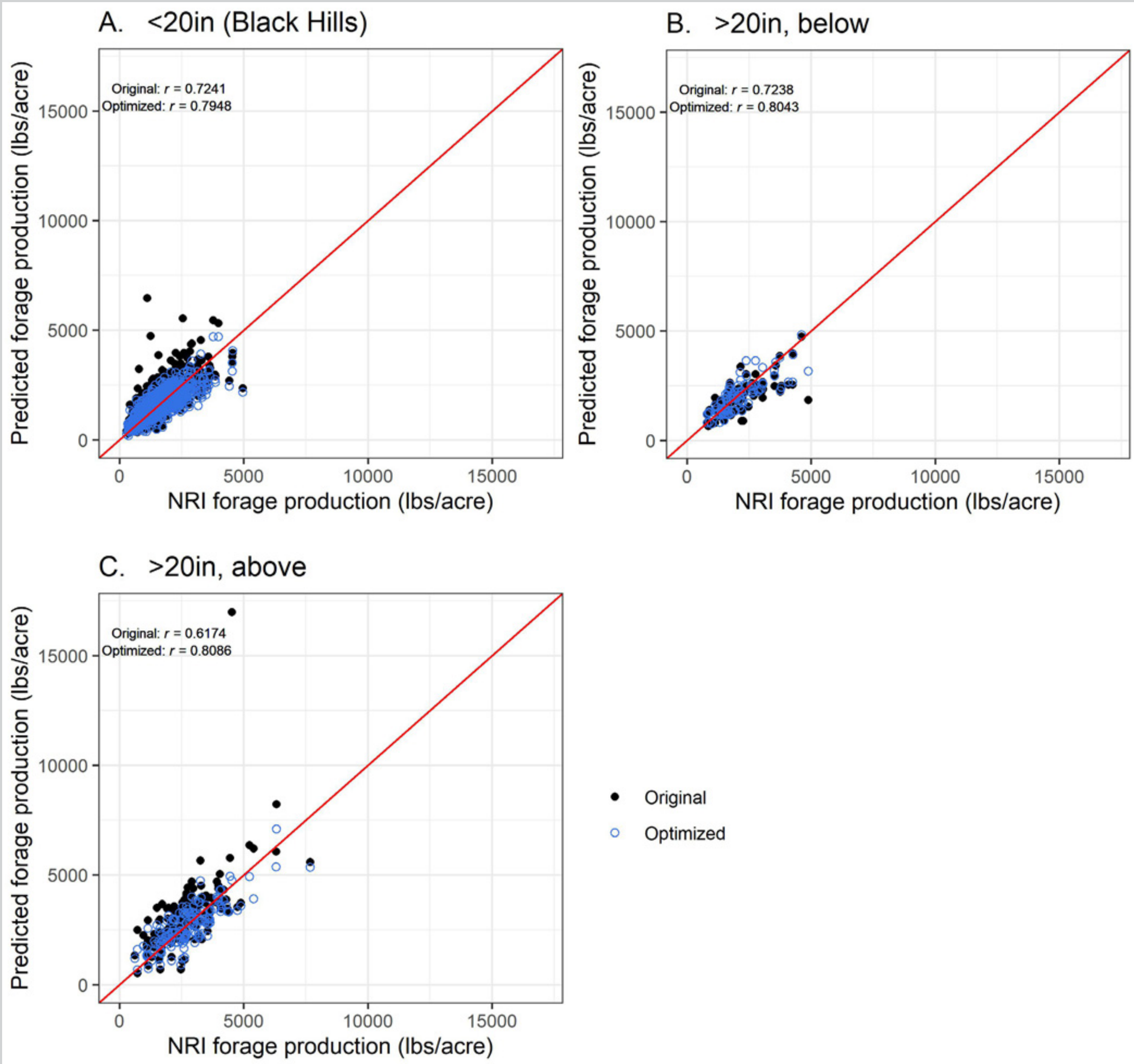


Figure 21—For each model (fig. 6), the SDDT forage prediction compared to actual forage production for original (solid black dots) and optimized (open-circle blue dots) SDDT including model results from each time period (month) estimating real-time predictions. The red diagonal line is the 1:1 line. This figure shows the actual forage production estimated from the NRI clipping data on the x-axis and the SDDT percent of normal estimate multiplied by the ESD representative value on the y-axis. The original model outlier in the ">20 in above" model (middle panel) was associated with very high October rainfall at the site. The optimized model did not produce a similar outlier.

Overflow and shallow ecological sites had severe overprediction at times, while clayey ecological sites tended to underpredict forage production in real time (fig. 22). Outlying points that were substantially overpredicting all occurred in the fall season (fig. 23). However, the optimization greatly improved these errors where the original mean absolute residual error for points in the fall season was 692 lbs and improved to 377 lbs with the optimized parameter values. Error differed across month of prediction with

July and November having the lowest error (fig. 24). The Black Hills had an average of 74.6 lbs error (4.4% error) as compared to 28.1 lbs (3.1% error) for locations outside the Black Hills (fig. 25).

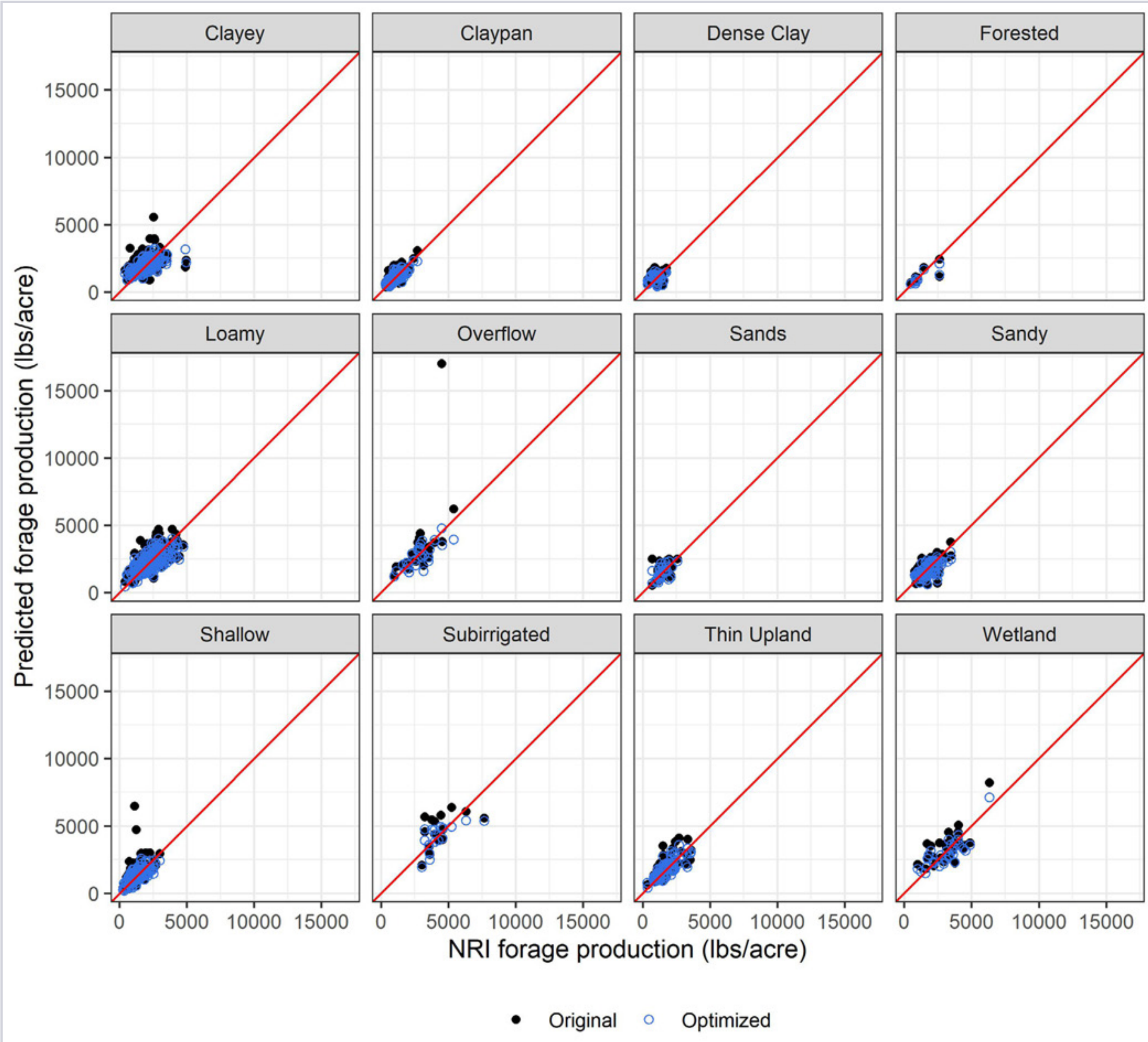


Figure 22—The SDDT forage prediction compared to actual forage production for the original (solid black dots) and optimized (open-circle blue dots) SDDT models subset by ESD for real-time predictions. The red diagonal line is the 1:1 line. This figure shows the actual forage production on the x-axis. The SDDT percent of normal estimate multiplied by the ESD representative value adjusted by growth curve is on the y-axis.

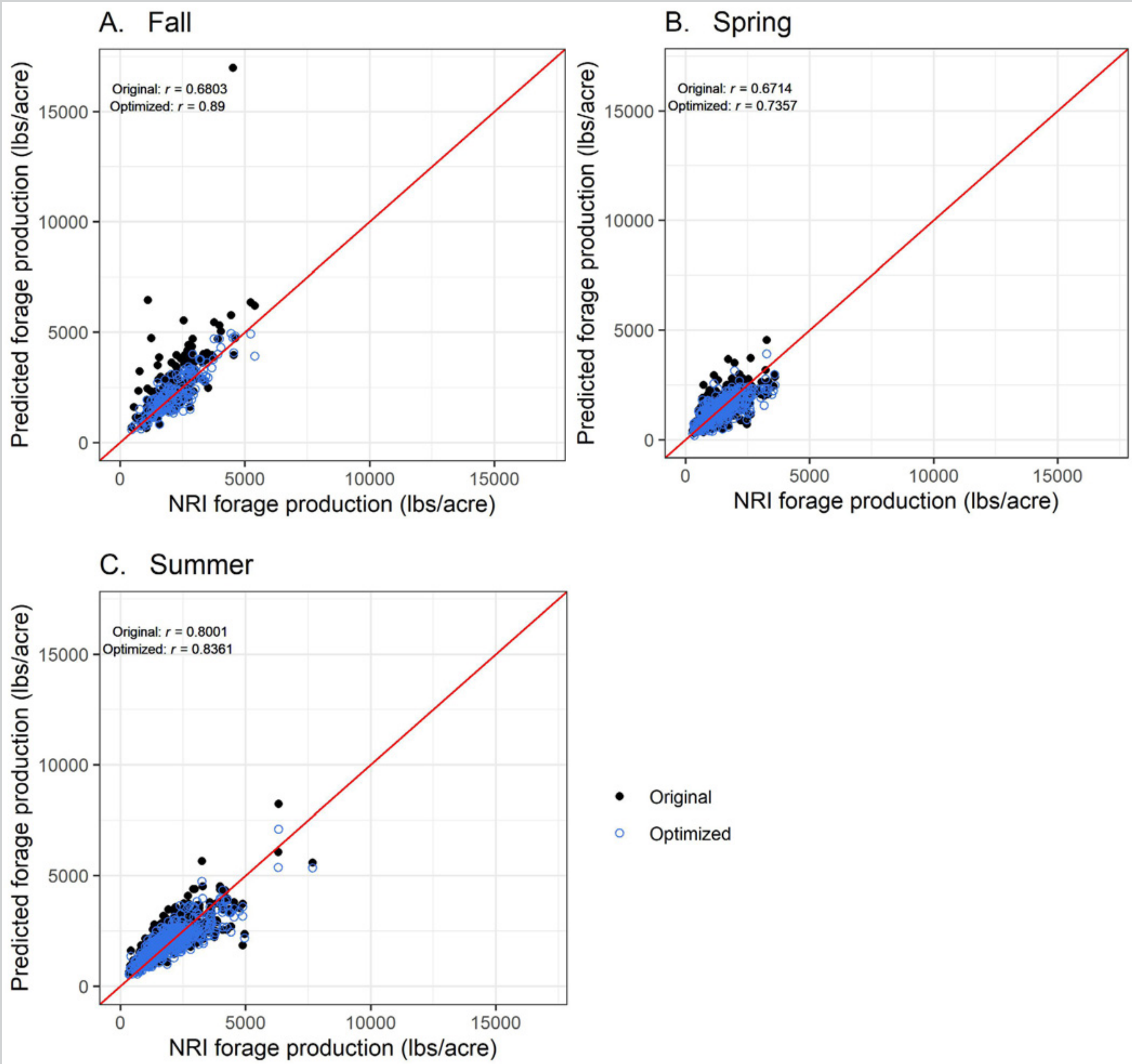


Figure 23—Predicted forage production (y-axis) versus actual forage production (x-axis) subset by season. Solid black dots and open circle blue dots are the original and optimized model predictions, respectively. The red diagonal line is the 1:1 line. The seasons that the NRI datapoints were harvested include fall (September–November, left panel), spring (May–June, middle panel), and summer (July–August, right panel).

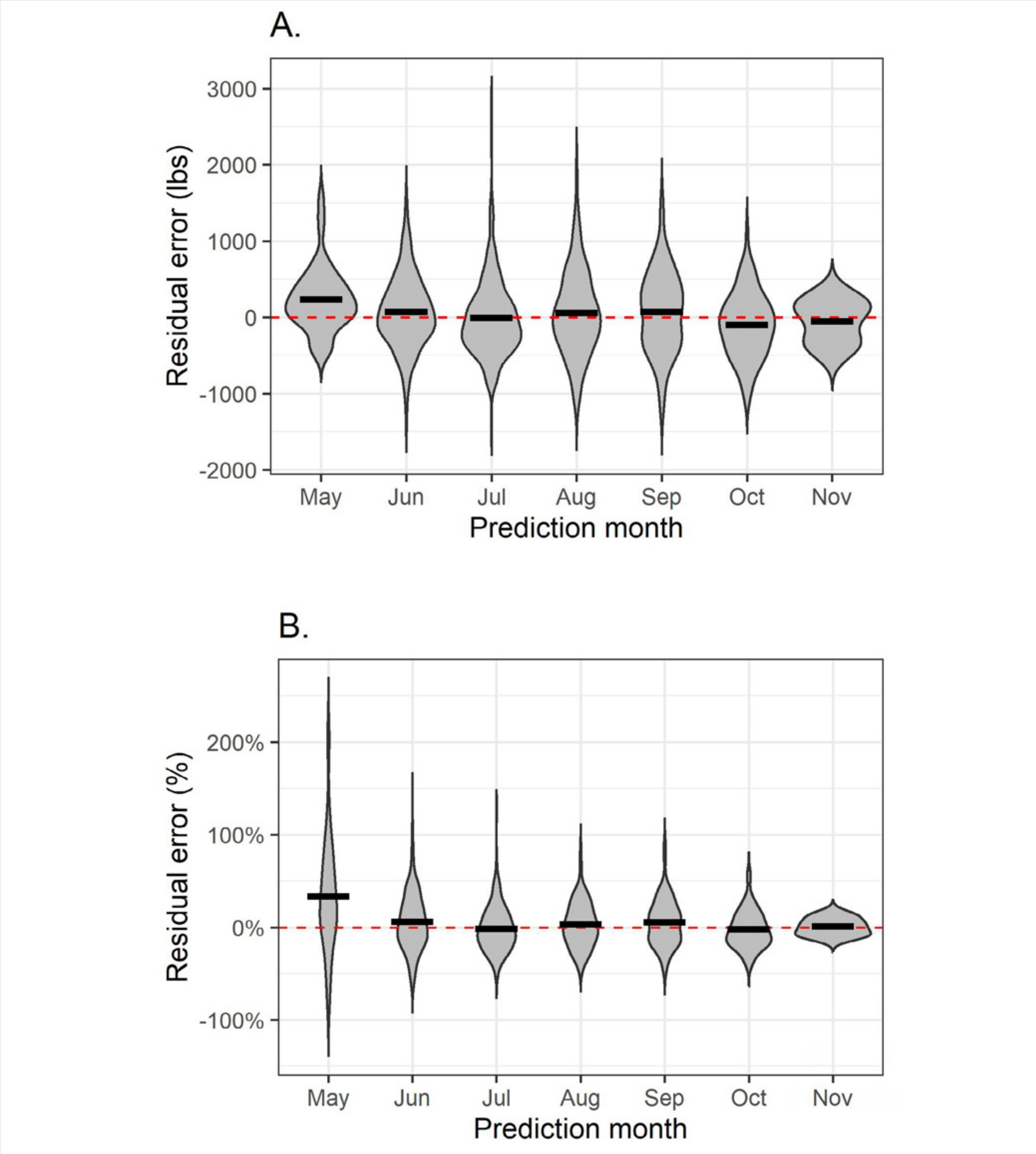


Figure 24—Residual error (observed-predicted) in pounds (left panel) and percent (right panel) for real-time forage predictions. The error in July (month 7) and November (month 11) appears to be closest to zero. The red horizontal line represents zero error, and the short black bars represent monthly mean error.

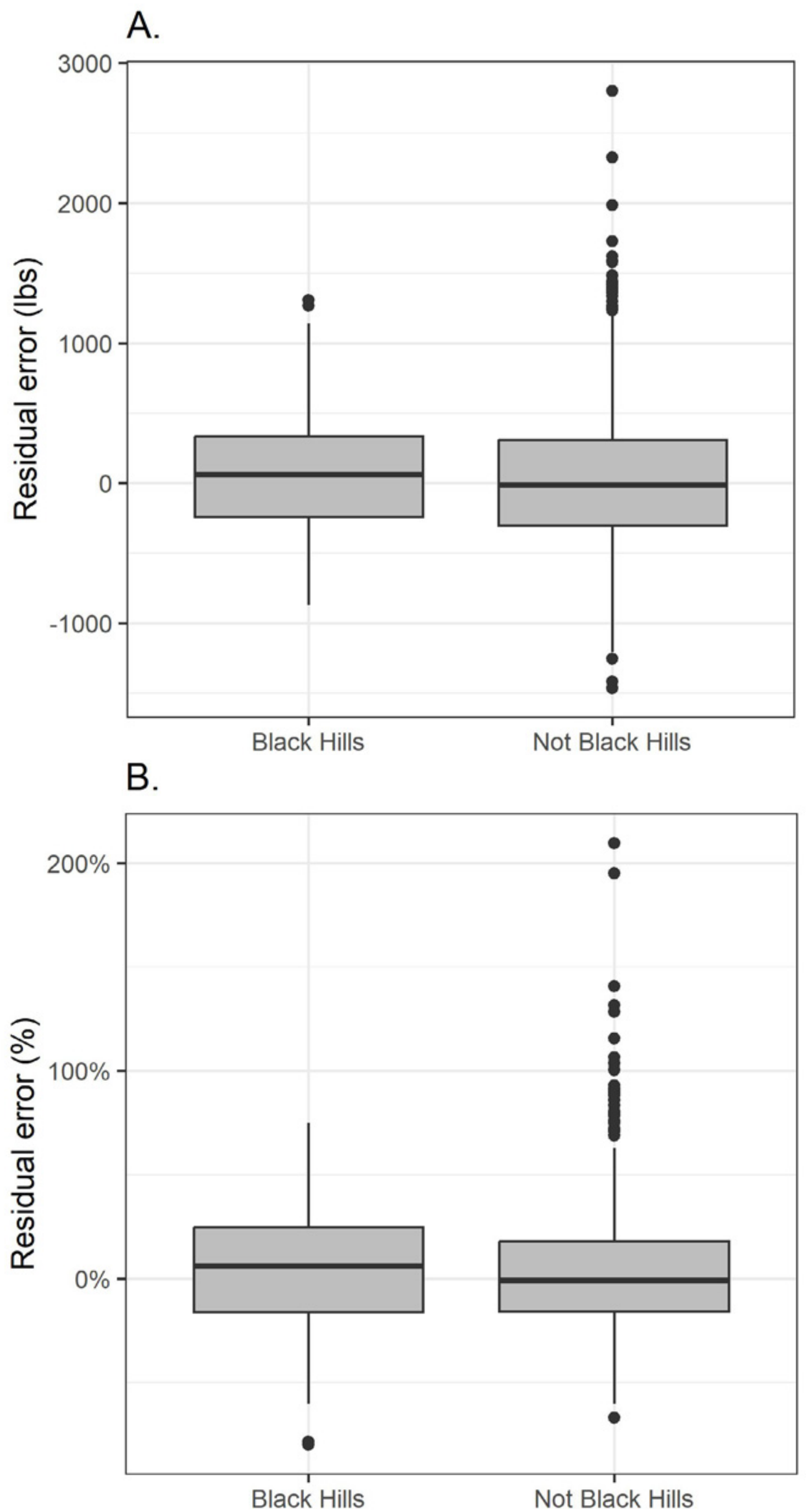


Figure 25—Real-time forage production error (observed-predicted; lbs and percentage on left and right panels, respectively) comparing the Black Hills to the rest of the State. Boxes represent the interquartile range (IQR) with a solid line representing the median and solid black whiskers extending to Q1-1.5*IQR and Q3+1.5*IQR. Outliers existing beyond the whiskers are shown by solid dots.

Summary results and discussion—

Optimization improved the monthly real-time predictions of forage production more than it improved the peak predictions of forage production. Therefore, the original peak prediction model was producing good estimates that were not much improved by the optimization. As peak predictions rely on historical data to fill in precipitation for missing months leading up to July (i.e., the time of peak prediction), the optimization of peak predictions is more difficult to improve, unlike the real-time predictions which use all current precipitation data and do not rely on historical values. Although optimized models have been created, both peak and real-time predictions have substantial uncertainty (+/– about 50% or ±1,000–1,100 lbs of forage,) but show no consistent bias in one direction or another. In our example above, which produced an expected percent of average forage production of 108 percent, the approximate uncertainty around that value would range from 58 percent to 158 percent. In application, the uncertainty of plus or minus 1,000 lb of forage roughly translates to a producer either needing to cull approximately one cow per acre or being able to add one cow per acre to their herd (assumes a 1,000 lb cow, with calf, or 913 lb air-dried forage needed per cow per month). Thus, the uncertainty in forage production and model optimization has economic implications.

The high margin of error in the SDDT comes from multiple sources (fig. 26). One source is the precision of the representative values of ESDs to portray the long-term forage production of each individual NRI point accurately. Representative Values from the Reference State were used as an estimate of long-term forage production at each site. Using the Representative Value of the Reference State means all sites were assumed to be in the Reference State or Reference Plant Community phase. Many sampled sites would be in some other plant community phase at the time of sampling (e.g., invaded). Because the NRI data do not identify which plant community phase was represented by the sample point, the appropriate plant community phase and subsequent representative production values would have required a detailed review of the species composition of each datapoint; this was beyond the scope of this validation effort. Future validation would benefit from having the ecological site's plant community phase identified in the NRI data set.

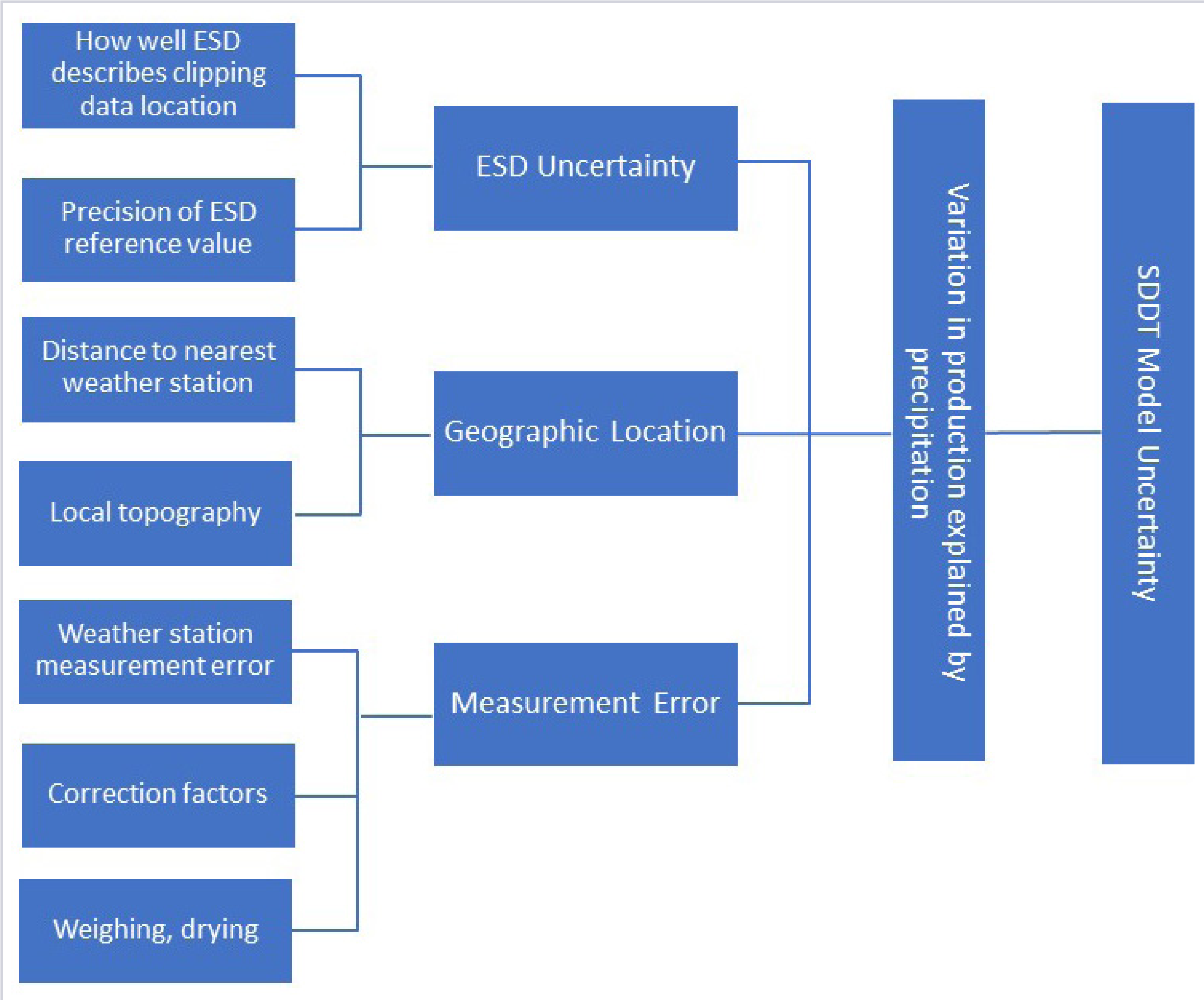


Figure 26—Hierarchical diagram of factors contributing to SDDT model uncertainty.

Another source of uncertainty is due to geographic location and the distance from the prediction point to the nearest weather station and local topography. This may result in inaccurate precipitation values used for prediction. Similarly, there may be errors within the weather stations themselves where precipitation is not measured correctly. There is also measurement error in the NRI and ESD values themselves due to weighing, drying, and the applied correction factors that are meant to account for grazing, seasonality and so on. Finally, there is uncertainty in correlating precipitation with forage production (i.e., the SDDT model itself). These different sources of uncertainty cannot be separated from the uncertainty associated with the SDDT precipitation-based model.

Although we found considerable model uncertainty, we did not find directional biases. Model error did not appear to show substantial bias either temporally or spatially. Additionally, peak prediction error did not greatly differ among the three sub-models, season, and above- versus below-average precipitation years (data not shown). It did differ slightly in the months leading up to July (i.e., the time of peak production) as error tended to gravitate more towards zero in May, June, and July (fig. 18). The real-time monthly prediction error differed by month; error was greater in the spring estimates compared to the fall estimates (fig. 24). However, weighting factors were not particularly robust in the optimization (i.e., values could moderately change with the addition or removal of observations), which implies the likelihood surface used was not smooth, and multiple combinations of different weighting values would produce similar results.

Spring precipitation is a driving factor in peak forage production (Wiles et al. 2011). Fall and spring weighting values for the peak predictions were rarely zero (table 2), but real-time monthly precipitation weights were more frequently zero (table S6), making the model predictions based solely on annual precipitation from the previous two years. Spring weighting factors appeared to play a more important role than fall weighting factors, as zeros were more likely to occur in the winter and fall months (table S6). As cool-season grass dominance usually peaks in production in the late spring and early summer (June–July), final production amounts may be more dependent on spring rather than summer rainfall (Heitschmidt and Vermeire 2006). Fall rainfall can help increase productivity by promoting early emergence and growth, which leads to increased C_3 perennial grass productivity when followed by an average or wet spring (Vermeire and Rinella 2020). However, fall rainfall can also increase productivity of undesirable nonnative winter annual grasses (Vermeire and Rinella 2020).

Moving forward: improving the SDDT—

Improved site-specific long-term productivity estimates would create a better validation dataset, which could be used to improve the SDDT. The SDDT is based on estimating the percent of average peak forage production by using the percent of average precipitation. To produce the percent of average precipitation, it is necessary to know the current precipitation and the long-term average precipitation. These values can be obtained with high confidence from weather stations and long-term weather data. To validate the SDDT by comparing the SDDT percent of normal precipitation to percent of average peak forage production, the values for current forage production and long-term average forage production are needed.

$$\frac{Current\ Precipitation}{Longterm\ Average\ Precipitation} = \frac{Current\ Forage\ Production}{Longterm\ Average\ Forage\ Production}$$

Improved site-specific long-term productivity estimates could be obtained through improved identification of ESD reference values associated with each site, repeated annual sampling of multiple sites, or satellite-calculated annual production estimates.

Proper identification of plant community states and phases could improve the validation dataset. The NRI data provided an estimate of current forage production data. However, the long-term average forage production for each NRI datapoint had to be based on the representative value from general ESDs, which may not capture the unique long-term forage production of each NRI datapoint. For example, if a pasture is partially invaded by cool-season Kentucky bluegrass (*Poa pratensis*), the pasture may have a long-term, higher average annual forage production than the representative value given in the ESD for that site.

This validation needed to use the ESD's general representative value because there was no way of knowing the long-term average annual forage production of each individual datapoint as NRI does not sample the same pastures each year. If we could remove this representative value error from the model, it is highly likely that precipitation values would be able to accurately predict forage production with a margin of error less than the current estimate of ±50 percent. However, obtaining this margin of error would require a dataset with more precise long-term average annual forage production values for sites spread across the South Dakota over multiple years as well as current forage values that were more directly measured and not corrected for factors such as grazing and seasonality.

Other potential validation datasets could be created. Repeated sampling of representative sites for multiple years across the State could also provide a validation dataset that would help improve the SDDT. This would take up to a decade to create and would require time-intensive labor to clip plots. Satellite normalized difference vegetation index (NDVI) may be another way to estimate long-term average production for individual sites (e.g., Rigge et al. 2013) and could be used to further validate the SDDT by having a more site-specific reference value than provided in ESDs. Annual biomass productivity has already been measured using NDVI in western South Dakota and could be used to develop long-term average biomass estimates (Rigge et al. 2013). However, NDVI estimation of herbaceous understory production may be difficult in forested systems like the Black Hills.

Using the SDDT in the context of other drought tools—

Grasslands can have widely varying biomass production from year to year as they respond to interannual variability in precipitation (Knapp and Smith 2001). Most drought tools focus on showing where drought is currently occurring (e.g., United States Drought Monitor (USDM); Svoboda et al. 2002), predicting drought based on precipitation or evaporative demand (e.g., Standardized Precipitation Index (SPI), Evaporative Demand Drought Index (EDDI)), or predicting drought based on soil moisture conditions (e.g., NLDAS Soil Moisture Drought Monitor, Evaporative Stress Index, Landscape Evaporative Response Index) (McKee et al. 1993; McEvoy et al. 2016; Rangwala et al. 2019). The SDDT takes drought prediction further by estimating the impact of drought on forage production and providing managers with a useful metric to help in decision making. The SDDT predicts grassland biomass production under the full range of precipitation levels that are known to occur, which benefits producers in both years of drought and years without drought. The SDDT is also known for its ease of use and is currently the only tool that incorporates a drought contingency plan building and storage capability.

In recent years, other vegetation production predictor tools have been developed, including Grasscast, the Rangeland Production Monitoring Service (RPMS), and the Rangeland Analysis Platform (RAP; Hartman et al. 2020; Jones et al. 2021; Peck et al. 2019; Reeves et al. 2021). These tools use satellite data such as NDVI in conjunction with weather, growth curves, and clipping data to calculate an estimate of percent of normal production. Grasscast provides imagery of estimated drought conditions with a resolution of 10-km2 pixels. Interestingly, estimates from the RPMS were correlated with NRI data from across the western U.S. with a correlation coefficient of 0.63 (Jones et al. 2021). This indicates that substantial variability is not explained by the NRI data and instead may be related to reasons we specified above. For comparison, our peak prediction correlation coefficient was 0.83. Overall, the SDDT is widely used by South Dakota's private and public land managers, despite the increased development of these additional vegetation production predictor tools. Further, the lessons we outline above in validating the SDDT should be considered in the development of other drought tools.

References

Albertson, F.W.; Weaver, J.E. 1946. Reduction of ungrazed mixed prairie to shortgrass as a result of drought and dust. Ecological Monographs. 16: 449–463. https://doi.org/10.2307/1961645

Byrd, R.H.; Lu, P. Nocedal; J. [et al.]. 1995. A limited memory algorithm for bound constrained optimization. SIAM Journal on Scientific Computing. 16: 1190–1208. https://doi.org/10.1137/091606

Conant, R.T.; Kluck, D.; Anderson, M.; [et al.]. 2018. Northern Great Plains. In: Reidmiller, D.R.; Avery, C.W.; Easterling, D.R.; [et al.], eds. Impacts, risks, and adaptation in the United States: Fourth National Climate Assessment. Washington, D.C.: U.S. Global Change Research Program: 941–986. https://repository.library.noaa.gov/view/noaa/19487 [Accessed 21 July 2025]

Epstein, H.E.; Lauenroth, W.K.; Burke, I.C. [et al.]. 1997. Productivity patterns of C-3 and C-4 functional types in the US Great Plains. Ecology. 78: 722–731. https://doi.org/10.1890/0012-9658(1997)078[0722:PPOCAC]2.0.CO;2

Hanson, C.L.; Kuhlman, A.R.; Lewis, J.K. 1978. Effect of grazing intensity and range condition on hydrology of western South Dakota ranges. Research Bulletins of the South Dakota Agricultural Experiment Station (1887–2011). 652. Brookings, SD: South Dakota State University. https://openprairie.sdstate.edu/agexperimentsta_bulletins/652/ [Accessed 21 July 2025]

Hartman, M.D.; Parton, W.J.; Derner, J.D.; [et al.]. 2020. Seasonal grassland productivity forecast for the U.S. Great Plains using Grass-Cast. Ecosphere .11: 23. https://doi.org/10.1002/ecs2.3280

Heisler-White, J.L.; Blair, J.M.; Kelly, E.F.; [et al.]. 2009. Contingent productivity responses to more extreme rainfall regimes across a grassland biome. Global Change Biology. 15: 2894–2904. https://doi.org/10.1111/j.1365-2486.2009.01961.x

Heitschmidt, R.K.; Vermeire, L.T. 2006. Can abundant summer precipitation counter losses in herbage production caused by spring drought? Rangeland Ecology and Management. 59: 392–399. https://doi.org/10.2111/05-164R2.1

Hoyt, J.C. 1936. Droughts of 1930–34. Water-Supply Paper 680. Washinton, DC: U.S. Department of Interior, Geological Survey. 106 p. https://pubs.usgs.gov/wsp/0680/report.pdf [Accessed 21 July 2025]

Jones, M.O.; Robinson, N.P.; Naugle, D.E. 2021. Annual and 16-day rangeland production estimates for the western United States. Rangeland Ecology and Management. 77: 112–117. https://doi.org/10.1016/j.rama.2021.04.003

Knapp, A.K.; Beier, C.; Briske, D.D.; [et al.]. 2008. Consequences of more extreme precipitation regimes for terrestrial ecosystems. Bioscience. 58: 811–821. https://doi.org/10.1641/B580908

Knapp, A.K.; Ciais, P.; Smith, M.D. 2017. Reconciling inconsistencies in precipitation-productivity relationships: Implications for climate change. New Phytologist. 214: 41–47. https://doi.org/10.1111/nph.14381

Knapp, A.K.; Smith, M.D. 2001. Variation among biomes in temporal dynamics of aboveground primary production. Science. 291: 481–484. https://doi.org/10.1126/science.291.5503.481

Lockwood, J.A.; Debrey, L.D. 1990. A solution for the sudden and unexplained extinction of the Rocky Mountain grasshopper (Orthoptera: Acrididae). Environmental Entomology. 19: 1194–1205. https://doi.org/10.1093/ee/19.5.1194

Luce, C.H.; Pedersen, N.; Campbell, J.; [et al.]. 2016. Characterizing drought for forested landscapes and streams. In: Vose, J.M.; Clark, J.S.; Luce, C.H.; [et al.], eds. Effects of drought on forests and rangelands in the United States: A comprehensive science synthesis. Washington, D.C.: U.S. Department of Agriculture, Forest Service: 13–48. https://research.fs.usda.gov/treesearch/52177 [Accessed 21 July 2025]

McEvoy, D.J.; Huntington, J.L.; Hobbins, M.T.; [et al.]. 2016. The Evaporative Demand Drought Index. Part II: CONUS-wide assessment against common drought indicators. Journal of Hydrometeorology. 17: 1763–1779. https://doi.org/10.1175/JHM-D-15-0122.1

McKee, T.B.; Doesken, N.J.; Kleist, J. 1993. The relationship of drought frequency and duration to time scales. In: Eighth Conference on Applied Climatology; 1993 January 17-22; Anaheim, CA. American Meteorological Society. pp. 179–184.

Nash, J.C.; Varadhan, R. 2011. Unifying optimization algorithms to aid software system users: Optimx for R. Journal of Statistical Software. 43: 1–14. https://doi.org/10.18637/jss.v043.i09

Nash, J.C. 2014. On best practice optimization methods in R. Journal of Statistical Software. 60: 1–14. https://doi.org/10.18637/jss.v060.i02

National Drought Mitigation Center. 2025. What is the USDM? Lincoln, NE: University of Nebraska-Lincoln, National Drought Mitigation Center. https://droughtmonitor.unl.edu/About/WhatistheUSDM.aspx [Accessed 3 February 2025]

Natural Resources Conservation Service Center for Survey Statistics and Methodology (NRCS CSSM). 2022. On-site data collection handbook of instructions. Iowa State University. https://grazingland.cssm.iastate.edu/site-data-collection-handbook-instructions [Accessed 3 February 2025]

NOAA National Integrated Drought Information System (NNIDIS). Current U.S. Drought Monitor Conditions for South Dakota. https://www.drought.gov/states/south-dakota [Accessed 21 July 2025]

Peck, D.E.; Derner, J.; Parton, W.J.; [et al.]. 2019. Flexible stocking with Grass-Cast: A new grassland productivity forecast to translate climate outlooks for ranchers. Western Economics Forum. 17: 24–39. https://waeaonline.org/western_econ_forum/flexible-stocking-with-grass-cast-a-new-grassland-productivity-forecast-to-translate-climate-outlooks-for-ranchers/ [21 Accessed July 2025]

Rangwala, I.; Smith, L.L.; Senay, G.; [et al.]. 2019. Landscape Evaporative Response Index (LERI): A high resolution monitoring and assessment of evapotranspiration across the contiguous United States. U.S. Geological Survey ScienceBase. https://doi.org/10.21429/43r4-3q68

Reece, P.E.; Alexander, J.D.; Johnson, J.R. 1991. EC91-123 Drought Management on Range and Pastureland: A handbook for Nebraska and South Dakota. Historical Materials from University of Nebraska–Lincoln Extension 1815. https://digitalcommons.unl.edu/extensionhist/1815/ [Accessed 21 July 2025]

Reeves, M.C.; Hanberry, B.B.; Wilmer, H.; [et al.]. 2021. An assessment of production trends on the Great Plains from 1984 to 2017. Rangeland Ecology and Management. 78: 165–179. https://doi.org/10.1016/j.rama.2020.01.011

Reichmann, L.G.; Sala, O.E.; Peters, D.P.C. 2013. Precipitation legacies in desert grassland primary production occur through previous-year tiller density. Ecology. 94:435–443. https://doi.org/10.1890/12-1237.1

Rigge, M.; Smart, A. B.; Wylie, B.T. [et al.]. 2013. Linking phenology and biomass productivity in South Dakota mixed-grass prairie. Rangeland Ecology and Management. 66:579–587. https://doi.org/10.2111/REM-D-12-00083.1

Sala, O.E.; Gherardi, L.A.; Reichmann, L.; [et al.]. 2012. Legacies of precipitation fluctuations on primary production: Theory and data synthesis. Philosophical Transactions of the Royal Society B. 367: 3135–3144. https://doi.org/10.1098/rstb.2011.0347

Sedivec, K.K.; Tober, D.A.; Duckwitz, W. 2007. Grasses for the Northern Plains: Growth patterns, forage characteristics and wildlife values. Volume I: Cool season. Extension R-1323. Fargo, ND. https://www.nrcs.usda.gov/sites/default/files/2022-10/ndpmcbk7681_Cool Season.pdf [Accessed 21 July 2025]

Sedivec, K.K.; Tober, D.A.; Duckwitz, W.L. 2009. Grasses for the Northern Plains: Growth patterns, forage characteristics and wildlife values. Volume II: Warm-season. Extension R-1390. Fargo, ND: North Dakota State University, NDSU Extension Service. 67 p. https://www.library.nd.gov/statedocs/NDSUExtensionService/r139020100504.pdf [Accessed 21 July 2025]

Smart, A. J.; Harmoney, K.; Scasta, J.D.; [et al.]. 2021. Forum: Critical decision dates for drought management in central and northern Great Plains rangelands. Rangeland Ecology and Management. 78: 191–200. https://doi.org/10.1016/j.rama.2019.09.005

Svoboda, M.; LeComte, D.; Hayes, M.; [et al.]. 2002. The Drought Monitor. Bulletin of the American Meteorological Society. 83: 1181–1190. https://doi.org/10.1175/1520-0477-83.8.1181

Teeri, J.A.; Stowe, L.G. 1976. Climatic patterns and distribution of C4 grasses in North America. Oecologia. 23:1–12. https://doi.org/10.1111/j.1461-0248.2007.01144.x

U.S. Environmental Protection Agency. 2010. Ecological Regions of North America Level II. https://www.epa.gov/eco-research/ecoregions-north-america

Vermeire, L.T.; Rinella, M.J. 2020. Fall water effects on growing season soil water content and plant productivity. Rangeland Ecology and Management. 73: 252–258. https://doi.org/10.1016/j.rama.2019.11.006

Weaver, J.E.; Albertson, F.W. 1943. Resurvey of grasses, forbs, and underground plant parts at the end of the great drought. Ecological Monographs. 13: 64–117. https://doi.org/10.2307/1943590

Wiles, L.J.; Dunn, G.; Printz, J. [et al.]. 2011. Spring precipitation as a predictor for peak standing crop of mixed-grass prairie. Rangeland Ecology and Management. 64: 215–222. https://doi.org/10.2111/REM-D-09-00024.1

Supplementary Material

Table S1—The 1991–2020 Monthly precipitation normals (in) for five locations across South Dakota.

Month	Brookings 2 NE	Interior 3 NE	Onida	Cottonwood 2E	Huron
January	0.43	0.46	0.54	0.41	0.58
February	0.5	0.55	0.79	0.56	0.75
March	1.06	1.16	0.97	1.03	1.15
April	2.17	2.26	1.96	1.96	2.52
May	3.45	3.62	3.17	2.9	3.15
June	4.29	3.46	3.63	3.09	3.89
July	3.61	2.23	2.52	2.1	2.83
August	3.22	1.81	2.51	1.63	2.59
September	3.1	1.39	1.78	1.22	2.43
October	1.97	1.59	1.93	1.46	1.95
November	0.8	0.53	0.68	0.54	0.82
December	0.61	0.54	0.59	0.48	0.66
Annual	24.6	19.6	21.07	17.38	23.32

Table S2—Percentage of annual rainfall (inches) occurring during the 8-month growing season (March–October) and during the 3-month spring and summer period (May–July). Percentages are based on values in table S1.

Growing Period	Brookings 2 NE	Interior 3 NE	Onida	Cottonwood 2E	Huron
March–October	93	89	88	89	88
May–July	59	48	44	47	42

S3—Historical development of the South Dakota Drought Tool (SDDT).

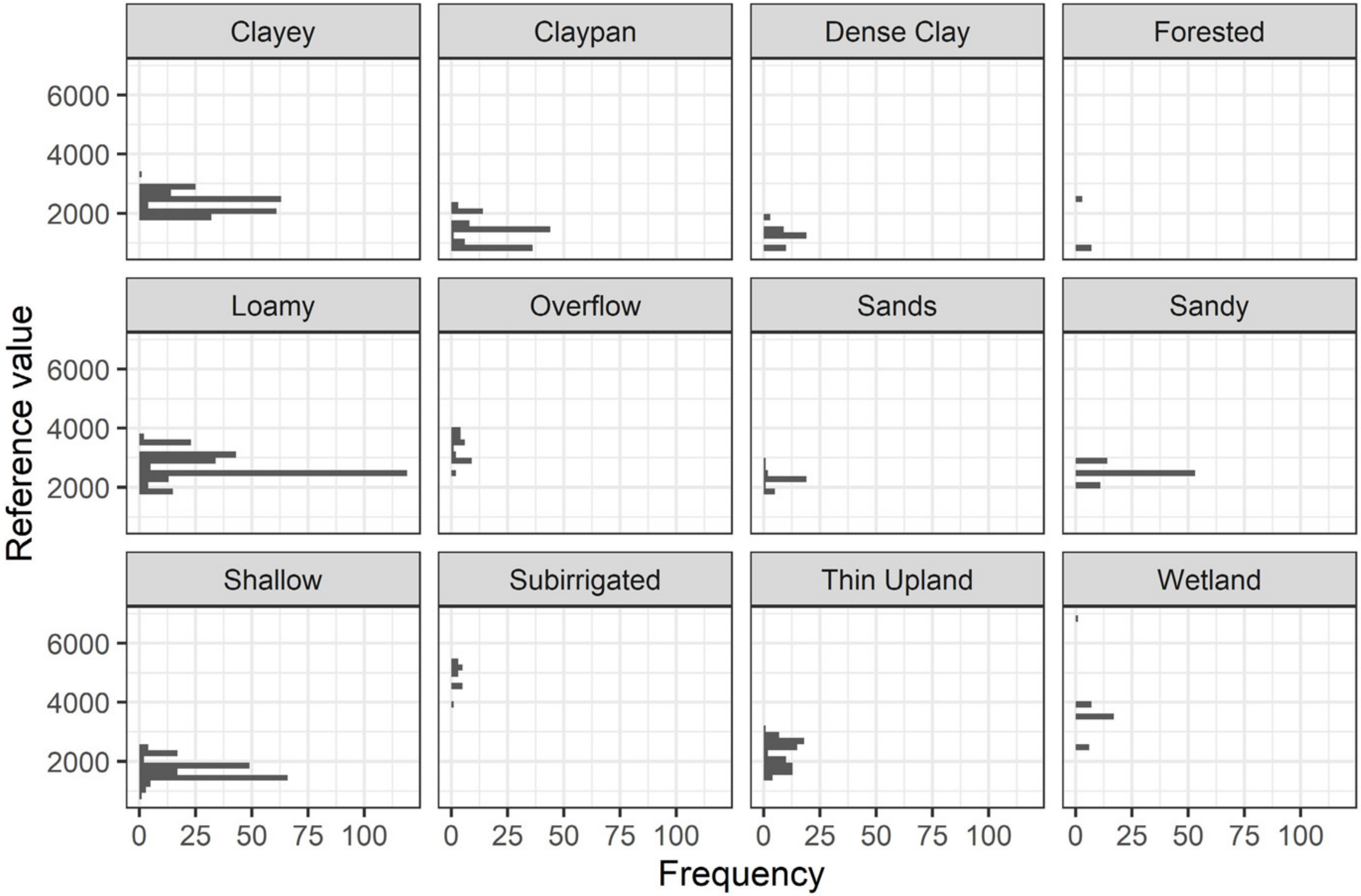
In 1999, an initial SDDT model based on the Cole model was developed to aid NRCS planners in determining how to adjust current year biomass clippings for below- and above- average growing seasons when calculating average annual production for native/natural grassland sites (known as the normal climate adjustment factor; USDA 1997). Several U.S. Department of Agriculture, Natural Resources Conservation Service (NRCS) employees suggested that livestock producers could benefit from using this tool as they prepared drought plans for their grazing operations. During the development of the SDDT model, U.S. Department of Agriculture, Agricultural Research Service scientist Gayle Dunn, who produced the NRCS Drought Calculator, collaborated with the SDDT model creators. The collaboration led to the incorporation of additional model factors, such as critical precipitation periods and above- and below-average precipitation years. The SDDT was user-friendly and gained broad regional acceptance with heavier use than national products (e.g., NRCS Drought Calculator). Additionally, in 2001, the SDDT was added to the South Dakota NRCS policy for producers to use for developing a contingency plan because of changes to the Prescribed Grazing Conservation Practice Standard.

S4—Precipitation (inches) values used in example from the Philip 2N weather station.

Amount of precipitation	June	July	Aug	Sept	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Sum
Historical Avg	3.19	1.82	1.53	1.18	1.21	0.37	0.39	0.3	0.32	0.8	1.57	2.99	15.67
Max Amt	7.337	4.186	3.519	2.714	2.783	0.851	0.897	0.69	0.736	1.84	3.611	6.877	NA
2013–2014	1.9	1.69	1.26	0.58	3.87	0.41	1.02	0.11	0.37	0.54	1.42	2.38	15.55
2014–2015	4	0.11	4.5	2.27	0.23	0.28	0.3	0.02	0.09	0.09	0.34	6.44	18.67

NA = not applicable

S5—Representative values according to Ecological Site Description (ESD). Frequency is equivalent to the number of datapoints. The ESDs are grouped by category, e.g., all clayey ESDs were grouped together. Note: Some ESDs had very few datapoints and unique ranges of Representative Values.



S-6

Table S-6.1—Original and optimized critical values and weighting factors for real-time predictions.

Critical Value	Model 1	Model 2	Model 3
Original	2.30	2.30	2.80
Optimized	1.52	5.02	1.89

Table S-6.2—Spring season weighting factors for model 1.

Critical Value	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Month 9	Month 10	Month 11	Month 12
Original	0	0	0.05	0.05	0.15	0.15	0.075	0.05	0.05	0	0	0
Optimized	0	0	0.05	0.05	1	0.0902	0.2112	0.297	0.2181	0.2341	0	0

Table S-6.3—Spring season weighting factors for model 2.

Critical Value	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Month 9	Month 10	Month 11	Month 12
Original	0	0	0.05	0.1	0.2	0.2	0.075	0.05	0.05	0	0	0
Optimized	0	0	0.05	0.1	0	0.2652	0.2848	0	0.05	0	0	0

Table S-6.4—Spring season weighting factors for model 3.

Critical Value	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Month 9	Month 10	Month 11	Month 12
Original	0	0	0.125	0.25	0.5	0.5	0.25	0.125	0.125	0	0	0
Optimized	0	0	0.125	0.25	0	0.0701	0.1059	0	0	0	0.2137	0

Table S-6.5—Fall season weighting factors for model 1.

Critical Value	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Month 9	Month 10	Month 11	Month 12
Original	0.0625	0.125	0.25	0.25	0.25	0.1875	0.1250	0.0625	0.125	0.1875	0.125	0.0625
Optimized	0.0625	0.125	0.25	0.25	0	0.2222	0.2269	0.1105	0	0	0	0.0625

Table S-6.6—Fall season weighting factors for model 2.

Critical Value	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Month 9	Month 10	Month 11	Month 12
Original	0	0	0	0	0	0	0	0	0	0	0	0
Optimized	0	0	0	0	0.5805	0.0411	0.0026	0.4195	0	0.087	0	0

Table S-6.7—Fall season weighting factors for model 3.

Critical Value	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Month 9	Month 10	Month 11	Month 12
Original	0.05	0.1	0.2	0.2	0.17	0.15	0.1	0.05	0.1	0.15	0.1	0.05
Optimized	0.05	0.1	0.2	0.2	0	0.3098	0.2036	0.0495	0.0096	0	0	0.05