Spring Precipitation as a Predictor for Peak Standing Crop of Mixed-Grass Prairie

L. J. Wiles,[1] Gale Dunn,[2] Jeff Printz,[3] Bob Patton,[4] and Anne Nyren[5]

Authors are [1]Weed Ecologist and [2]Soil Scientist, US Department of Agriculture–Agricultural Research Service, Fort Collins, CO 80526, USA; [3]Range Conservationist, US Department of Agriculture–Natural Resources Conservation Service, Bismarck, ND 58504, USA; and [4]Range Scientist and [5]Science Administrator, North Dakota State University, Streeter, ND 58483, USA.

Abstract

Ranchers and range managers need a decision support tool that provides a reasonably accurate prediction of forage growth potential early in the season to help users make destocking decisions. Erroneous stocking rate decisions can have dire economic and environmental consequences, particularly when forage production is low. Predictions must be based on information that is easily obtained and relevant to the particular range. Our goal was to evaluate monthly precipitation in spring months as a potential predictor of forage production compared to annual and growing-season precipitation. We analyzed the relationships between grazed and ungrazed peak standing crop (PSC) and precipitation using nonlinear regression and a plateau model, Akaike's information criterion for model selection, and data from three locations: Streeter, North Dakota; Miles City, Montana; and Cheyenne, Wyoming. The plateau model included a linear segment, representing precipitation limiting production, and a plateau, an estimate of average production when precipitation is no longer the limiting factor. Both the response and predictor variables were rescaled so variability in production from average production was related to variability in precipitation from the long-term average. We found that grazing did not affect the relationship between PSC and precipitation, nor were annual or growing-season precipitation good predictor variables. The best predictor variable was total precipitation in April and May for Montana, May and June for North Dakota, and April, May, and June for Wyoming, with r^2 ranging from 0.74 to 0.79 for precipitation less than long-term average. These results indicate that spring precipitation provides useful information for destocking decisions and can potentially be used to develop a decision support tool, and the results will guide our choice of possible predictor models for the tool.

Resumen

Los ganaderos y los manejadores de pastizales necesitan una herramienta de apoyo para hacer una predicción razonable y precisa del potencial de crecimiento del forraje al inicio de la estación para ayudar a los usuarios a tomar decisiones en reducir el número de animales. Las decisiones erróneas de la carga animal pueden tener graves consecuencias económicas y ambientales, especialmente cuando la producción de forraje es baja. Las predicciones deben basarse en información que se obtenga fácilmente y sea adecuada al pastizal en particular. Nuestro objetivo fue el evaluar la precipitación mensual durante la primavera como un predictor potencial de la producción de forraje en comparación con la precipitación anual y de la época de crecimiento. Analizamos la relación entre áreas pastoreadas y no pastoreadas con la producción de forraje (PSC) al final de la época de crecimiento y también con la precipitación utilizando modelos de regresión no linear y utilizando el criterio de la información de Akaike para la selección de un modelo, y datos provenientes de tres localidades: Streeter, ND, Miles City, MT, and Cheyenne, WY. En el modelo de regresión usó un segmento linear, representando la precipitación que limita la producción, y la regresión con una estimación de la producción promedio cuando la precipitación ya no es el factor limitante. Ambas respuestas y las variables de predicción se modificaron a una escala de manera que la variabilidad de la media de producción se relacionara con la variabilidad en la precipitación promedio a largo plazo. Encontramos que el pastoreo no afectó en la relación entre PSC y la precipitación, tampoco la precipitación anual o de la época de crecimiento fueron buenas variables de predicción. La mejor variable de predicción fue la precipitación total en Abril y Mayo para MT, Mayo y Junio para ND y Abril, Mayo y Junio para WY, con rango en r^2 de 0.74 a 0.79 para la precipitación menor que la del promedio a largo plazo. Estos resultados indican que la precipitación de primavera es una información útil para tomar decisiones sobre el desalojamiento del ganado y puede ayudar a la toma de decisiones, y los resultados deben guiar la opción de los modelos posibles de predicción como herramienta.

Key Words: Akaike's information criteria, decision support tools, rangeland drought, stocking decisions

INTRODUCTION

Ranchers and range managers need a decision support tool that provides the user with a reasonably accurate prediction of forage growth potential as early as possible in the coming growing/grazing season (Smoliak 1986). Stocking or destocking decisions need to be made before the final forage production level is known, and erroneous stocking rate decisions can have dire economic and environmental consequences. A major

Research was funded in part by the US Department of Agriculture–Risk Management Agency, RFA-5084 Agreement Number 05IE08310221.

Mention of a proprietary product does not constitute a guarantee or warranty of the product by USDA or the authors and does not imply its approval to the exclusion of other products that also may be suitable.

Correspondence: Gale Dunn, Agricultural Systems Research Unit, US Department of Agriculture–Agricultural Research Service. 2150 Centre Ave., Building D, Suite 200, Fort Collins, CO 80526, USA. Email: gale.dunn@ars.usda.gov

Manuscript received 20 March 2009; manuscript accepted 6 December 2010.

problem faced by grazing managers is annual variation in forage production due to climate (Vallentine 2001). To help managers with stocking decisions, the tool will need a climate variable that has a sound scientific relationship with forage growth and is easily obtained and relevant to the particular range.

Precipitation is a climate variable that meets these three criteria as a predictor in decision tools. Precipitation values can be found in newspapers, on television, or on the Internet. Precipitation data can be easily collected by individuals to ensure the data is closely associated with the range in question. A sound scientific relationship between forage growth and precipitation has long been established (Dahl 1963; Currie and Peterson 1966; Lauenroth and Whitman 1977; Sims and Singh 1978; Smoliak 1986; Lauenroth and Sala 1992; Briggs and Knapp 1995; Epstein et al. 1996; Frank et al. 1996; Oesterheld et al. 2001; Heitschmidt et al. 2005; Schwinning et al. 2005). In this study, we investigated the potential to predict forage growth potential for stocking and destocking decisions from this readily available climate variable.

More than just precipitation is involved in forage growth. Grazing management, prolonged drought, and soil type also can have profound effects on the forage growth in any particular year (Lauenroth and Whitman 1977; Briggs and Knapp 1995; Frank et al. 1996; Gillen and Sims 2006; Marques da Silva et al. 2008). Temperature highs and lows play a large role in forage growth (Briggs and Knapp 1995; Epstein et al. 1996; Frank et al. 1996; Bartholomew and Williams 2005). Although some studies have shown that less than 50% ($r^2 < 0.50$) of annual variability in forage production is due to precipitation (Briggs and Knapp 1995; Oesterheld et al. 2001; Smart et al. 2007), other studies have found the relationship to account for greater than 50% of variability (Dahl 1963; Currie and Peterson 1966; Smoliak 1986; Derner and Hart 2007; Smart et al. 2007).

Although annual precipitation is a convenient measure for studies relating forage production and precipitation, it ignores the reality that some of the annual precipitation falls when the forage plant is senescing, dormant, or becoming dormant, or when the ground on which the precipitation falls is frozen or already covered with snow or ice. For this reason, many researchers have narrowed their evaluation of the effects of precipitation on forage production to precipitation that falls either during the entire growing season or just during spring months (Smoliak 1986; Lauenroth and Sala 1992; Heitschmidt et al. 2005; Schwinning et al. 2005; Derner and Hart 2007; Smart et al. 2007). This indicates the potential to predict forage growth from precipitation data collected before stocking rate decisions must be made.

These studies have shown good relationships between precipitation and forage production, but even when using monthly precipitation totals during the growing season, there are limits to correlation with forage growth. The sum total of monthly precipitation indicates nothing about the distribution or intensity of the precipitation within the month. Daily precipitation records provide a finer resolution of measurement of intensity and duration than monthly records. However, more detailed precipitation data are potentially no better than a monthly total unless related to infiltration potential of soil. Further, entry of daily rather than monthly precipitation data is more time consuming for the user. For these reasons, we began our search for a precipitation-based predictor of forage growth for a decision tool by investigating the relationship between monthly precipitation and forage growth.

Table 1. Forage production and precipitation at the three locations of the study. Precipitation is described in terms of predictor variables of regression models.

	Location		
	Montana (8 yr)	North Dakota (17 yr)	Wyoming (15 yr)
	Mean (SD)		
PSC ($kg \cdot ha^{-1}$)			
Ungrazed	1 700 (208)	2 687 (126)	1 500 (159)
Grazed	1 583 (294)	2 810 (159)	1 193 (118)
Precipitation (cm)			
Annual (January through December)	31.92 (2.23)	47.00 (2.66)	39.10 (2.85)
Growing season (April through October)	26.73 (2.19)	40.93 (2.46)	32.37 (2.87)
January–June	17.67 (1.45)	22.28 (1.58)	21.50 (1.88)
April–May	8.11 (1.02)	9.80 (1.24)	10.71 (1.50)
April–May–June	14.04 (1.30)	18.62 (1.51)	17.06 (1.94)
May–June	10.68 (1.66)	15.52 (1.57)	12.57 (1.73)

The objective of this study was to identify the best predictor variables, based on monthly spring precipitation, and the best functional form for a model to estimate mixed-grass prairie peak standing crop (PSC). The models specified either a linear or nonlinear relationship between precipitation and forage production, and the candidate predictor variables were the sum of precipitation during 2 or 3 mo early in the growing season. We hypothesized average precipitation would result in average production and the best predictor variable comprised of monthly spring precipitation would vary with location and intensity of grazing, and we investigated whether total monthly precipitation in early spring is a better predictor than is total growing-season precipitation.

METHODS

In this study, the relationship between precipitation and forage production was investigated with PSC and precipitation data from three locations. Models of the relationships were compared using an information-theoretic approach for model selection.

Data

Three locations, with data sets including ungrazed and grazed treatments covering 8 yr to 17 yr, were chosen for analysis (Table 1). The Central Grasslands Extension Research Center (CGERC) near Streeter, North Dakota, is at an elevation of around 607 m and has an average annual precipitation rate of 43.4 cm, 80% of which falls between 1 April and 30 September (NDAWN 2008). The native range at the research center is described as a mixed-grass prairie with *Poa pratensis* L., *Agropyron smithii* Rydb., *Stipa viridula* Trin., *Carex heliophia* Mack., and *Carex obtusata* Lilj. as the dominant grasses (Biondini et al. 1998). Biondini et al. (1998) provide a detailed description of the topography, soil morphology, climate, and range. Since a single source of monthly precipitation values for these forage data was not available, we constructed a precipitation data set with information from three sources: CGERC, the North Dakota Agricultural Weather Network (NDAWN 2008), and the Western Regional Climate Center (WRCC 2008). Long-term precipitation data were from the NDAWN 2008 source.

The Keogh Livestock and Range Research Laboratory is near Miles City, Montana. Miles City has an elevation of approximately 722 m and a long-term annual precipitation total of 34.0 cm, 60–70% of which falls between mid-April and mid-September (Eneboe et al. 2002). The dominant native grasses on this mixed-grass prairie are described by Eneboe et al. (2002) as a "grama–needlegass–wheatgrass (*Bouteloua, Stipa, Agropyron*) mix." Eneboe et al. (2002) provide a detailed description of the study location including experimental design of the research location, soils, and climate. The precipitation data for this location, both monthly for the study period and long-term averages, are from the WRCC (2008).

The High Plains Grassland Research Station is near Cheyenne, Wyoming. The elevation of Cheyenne is 1 850 m. The long-term average annual precipitation is 38.1 cm, 80% of which falls between 1 April and 30 September (WRCC 2008). According to Derner and Hart (2007), the dominant native grasses on this mixed-grass prairie are western wheatgrass (*Agropyron smithii*), needle-and-thread (*Stipa comata*), prairie junegrass (*Koeleria macranatha* [Ledeb.] J.A. Schultes), and blue grama (*Bouteloua gracilis* [H.B.K.] Lag. ex Griffiths). The data used in this study were also used by Derner and Hart (2007). Their detailed description of the study location and data collection technique are not repeated here. All precipitation data, both monthly and long-term, were collected at the research station.

Models

It is desirable to develop a decision support tool for ranchers and range managers that is readily transferable to different parts of the Great Plains and to the many associated ecosystems. However, the amount of production per unit of precipitation varies with differences in average production and average precipitation among locations. Consequently, our analysis differs from much previous research relating forage growth and precipitation in that we rescaled both the response variable and the predictor variables. With rescaling, the variability of forage production from average production is related to the variability of precipitation from long-term average precipitation

$$\mathrm{PSC_R} = f(\mathrm{P_R}) \qquad [1]$$

where $\mathrm{PSC_R}$ is rescaled PSC and $\mathrm{P_R}$ is rescaled total precipitation for some period.

We rescaled precipitation ($\mathrm{P_R}$) by dividing the total precipitation for some period ($\mathrm{P_P}$) for a location by the long-term average precipitation ($\mathrm{P_{mean}}$) for that location

$$\mathrm{P_R} = \frac{\mathrm{P_P}}{\mathrm{P_{mean}}} \qquad [2]$$

We did not have similar long-term averages for PSC, so PSC for a location was rescaled by dividing each data value by the mean of the data set:

$$\mathrm{PSC_R} = \frac{\mathrm{PSC}}{\mathrm{PSC_{mean}}} \qquad [3]$$

Underlying this rescaling is our hypothesis that average precipitation ($\mathrm{P_R} = 1$) will result in average PSC ($\mathrm{PSC_R} = 1$).

Assuming that stocking decisions would be made before July, the potential predictor variables for representing early growing-season precipitation were rescaled total precipitation from four different time periods within the period from January to June. These were January through June ($\mathrm{P_{JanJun}}$), April through May ($\mathrm{P_{AprMay}}$), April through June ($\mathrm{P_{AprMayJun}}$), and May through June ($\mathrm{P_{MayJun}}$) (Table 1). We also evaluated annual ($\mathrm{P_{Annual}}$) and growing-season ($\mathrm{P_{Grow}}$) precipitation as predictor variables. Growing season for all three mixed-grass prairie locations was considered to be April through September. All of our data sets included ungrazed and grazed treatments so we included an indicator variable for grazing in some models to evaluate whether the best predictor variable differed with the intensity of grazing.

The relationship between precipitation and PSC was initially modeled assuming a typical relationship between plant productivity and an environmental resource. Plant productivity increases in proportion to availability of a resource until an optimum quantity of the resource is reached (Radosevich and Holt 1984). Beyond that level, more of the resource does not increase productivity. There are many ways to represent this relationship. We used a broken-line plateau regression equation with a linear relationship between the response and predictor variables until the response reached a plateau:

$$\begin{aligned} \mathrm{PSC}_{R_i} &= a + b \cdot \mathrm{P}_{R_i} \quad \textit{if}\ \mathrm{P}_{R_i} < \mathrm{P}_{R_\pi} \\ \mathrm{PSC}_{R_i} &= \pi \quad \textit{if}\ \mathrm{P}_{R_i} \geq \mathrm{P}_{R_\pi} \end{aligned} \qquad [4]$$

In this equation, *a* is the intercept and *b* is the slope of the linear segment of the model, π is the plateau and P_{R_π} is the amount of precipitation at which the plateau is reached.

The amount of precipitation at which the plateau is reached (P_{R_π}) is related to the parameters of the linear segment of the regression equation:

$$\mathrm{P}_{R_\pi} = \frac{(\pi - a)}{b} \qquad [5]$$

To determine if grazing influenced the relationship between PSC and precipitation, we used a model with an indicator variable for grazing (G).

$$\begin{aligned} \mathrm{PSC}_{R_i} &= a + G \cdot a_G + (b + G \cdot b_G) \cdot \mathrm{P}_{R_i} \quad \textit{if}\ \mathrm{P}_{R_i} < \mathrm{P}_{R_\pi} \\ \mathrm{PSC}_{R_i} &= \pi + G \cdot \pi_G \quad \textit{if}\ \mathrm{P}_{R_i} \geq \mathrm{P}_{R_\pi} \end{aligned} \qquad [6]$$

In this equation, $G = 1$ for PSC under grazing and $G = 0$ without grazing. This model allowed the slope and intercept of the linear segment of the model and the plateau and the amount of precipitation at which the plateau was reached to be different with and without grazing.

The parameters and standard errors of equations 4 and 6 were estimated using Fieller's method and nonlinear ordinary least squares regression (Kendall and Stuart 1969). In some cases, particularly with the data from Montana, difficulty in fitting the equation indicated the model (equation 4 or 6) had too many parameters. Consequently, we estimated linear as well as nonlinear equations for all predictor variables and all locations:

$$\mathrm{PSC}_{R_i} = a + b \cdot \mathrm{P}_{R_i} \qquad [7]$$

Or, with the indicator variable,

$$\mathrm{PSC}_{R_i} = a + G \cdot a_G + (b + G \cdot b_G) \cdot \mathrm{P}_{R_i} \qquad [8]$$

In all, 12 models were fitted for each location (six precipitation variables, with and without an indicator variable for grazing).

Model Comparison

We compared the models for a location using a model selection procedure from information theory. This method is recommended for observational data and has commonly been used to compare regression equations that represent mechanistic models of ecological theory (Richards 2005). Moreover, this approach for evaluating models and selecting predictor variables is the most appropriate for the ultimate objective of this research, a decision support tool. Although a reasonably accurate prediction of forage production is needed for a decision tool, prediction accuracy is just one characteristic that will guide choice of the information and model for predicting forage production; trade-offs between accuracy and other desirable characteristics of a decision tool also need to be considered. The information theory method allows ranking of models from best to worst, as well as scaling to identify models that are similar or very different in fitting the data (Anderson et al. 2000).

The criterion for selecting and evaluating models is Akaike's information criteria (AIC). Readers are referred to Anderson et al. (2000) and Richards (2005) for detailed description of the theory on which AIC is based. Briefly, this criterion is based on Kullback–Leibler information, a measure of the information lost when approximating reality with a model. A good model minimizes the loss of information, but, of course, reality is not known. AIC is an approximation of Kullack–Leibler information when using maximum likelihood to estimate a model. This is a relative measure. An individual value of AIC for a model and data set has no meaning, but AIC values for a set of models indicate loss of information compared to reality among the set of models. That is, AIC values are relative measures of the support, or evidence, for each model given the data and consequently, the relative value of the models for inference. The models may be of different types, but all models must have the same response variable and be applied to the same data set. The model with the lowest AIC is the best inference, or hypothesis, given the set of models and the data.

Our evaluation of models is based on a version of AIC that includes a correction for bias of AIC when applied to small data sets ($\mathrm{AIC_c}$). Although $\mathrm{AIC_c}$ was developed for maximum likelihood estimation, when using least squares regression with normally distributed errors, AICc can be calculated as

$$\mathrm{AIC_c} = n \cdot \ln(\mathrm{SSE}/n) + 2K + 2K \cdot (K+1)/(n-K-1) \qquad [9]$$

where n is the number of observations, K is the number of parameters estimated in fitting the model and SSE is the estimated sum of squared errors (Anderson et al. 2000). Models can be ranked from best (lowest) to worst (highest) based on $\mathrm{AIC_c}$ values, but additional measures must be calculated for a more quantitative comparison of models. The AIC difference (Δ) is the difference between the AIC value of a model and the minimum AIC value among all of the models for that dataset:

$$\Delta_i = \mathrm{AIC}_{c_i} - \text{minimum } \mathrm{AIC_c} \qquad [10]$$

An Akaike weight is the ratio of the AIC difference of a model compared to sum of the AIC differences of all models. This is a rescaling of AIC differences to a maximum value of 1. The Akaike weight for model i is calculated as

$$w_i = \frac{exp\left(-\frac{1}{2} \cdot \Delta i\right)}{\sum_{r=1}^{R} exp\left(-\frac{1}{2} \cdot \Delta r\right)} \qquad [11]$$

where R is the number of models in the set. The ratio of Akaike's weights of two models (w_i/w_r) is the evidence ratio. An evidence ratio of "x" for model i indicates that model i is "x" times more likely than model r to be the best in the set of R candidate models given the data.

We calculated two measures of model fit, r^2 and d, for the highest AIC-ranked model for each location. The coefficient of determination, calculated as the square of the correlation of the observed and predicted values, is an estimate of the proportion of the variation in observations that is explained by the model. The index of agreement (d), proposed by Willmott (1981) was also calculated from the observed and predicted values:

$$d = 1 - \left[\frac{\sum_{i=1}^{n} (p_i - o_i)^2}{\sum_{i=1}^{n} \left(|p'_i| + |o'_i|\right)^2}\right] \qquad 0 \le d \le 1 \qquad [12]$$

where p_i is predicted value, o_i is observed value, $p'_i = p_i - \bar{o}$, $o'_i = o_i - \bar{o}$, and $\bar{o}$ is the mean of observed values.

This index of agreement is a measure of the how well observed values are predicted. If predicted values are plotted against the observed values, d is a measure of how close the points are to a 1:1 line. The value of d is equal to 1 for perfect agreement (all points falling on the 1:1 line). Because the plateau of the nonlinear model indicates that additional precipitation does not influence production, we calculated values of r^2 and d for the linear segment of the model as well as for the entire regression model.

RESULTS AND DISCUSSION

Ranking of Models

Comparison of the models based on AIC are shown in Table 2 with only the best-fitting form of the model (linear or nonlinear) shown for each predictor variable. The lowest value of AIC for a

Table 2. Ranking of the models of the relationship between forage production and annual, growing season or spring precipitation. Reported values are the number of model parameters (K) and corrected Akaike's information criterion (AIC_c), Akaike differences (Δ_i) and weights (w_i), and the ratio of the maximum w_i for the set of models over w_i (evidence ratio). The models are listed from "best" to "worse" by AIC.

Location	Model[1]	Predictor variables[2]	K[3]	SSE	AIC_c	Δ_i	w_i	Evidence ratio
Montana	Plateau	April–May	4	0.65	−35.2	0	0.826	1
	Linear	January–June	3	1.22	−29.5	5.7	0.048	17
	Linear	April–May–June	3	1.47	−26.7	8.5	0.012	69
	Linear	May–June	3	1.71	−24.4	10.8	0.004	222
	Linear	*G*, April–May	5	1.09	−22.6	12.6	0.002	527
	Linear	Annual	3	2.01	−21.9	13.3	0.001	745
	Linear	Growing season	3	2.04	−21.8	13.4	0.001	813
	Linear	*G*, January–June	5	1.21	−21.1	14.1	0.001	1 110
	Linear	*G*, April–May–June	5	1.44	−18.5	16.7	< 0.001	4 120
	Linear	*G*, May–June	5	1.70	−16.0	19.2	< 0.001	14 429
	Linear	*G*, growing season	5	1.94	−14.1	21.1	< 0.001	38 465
	Linear	*G*, annual	5	1.95	−14.0	21.2	< 0.001	40 175
North Dakota	Plateau	May–June	4	0.73	−121.4	0	0.639	1
	Plateau	January–June	4	0.76	−119.7	1.7	0.276	2
	Plateau	Growing season	4	0.86	−115.7	5.7	0.036	18
	Plateau	April–May–June	4	0.90	−114.2	7.2	0.017	37
	Plateau	*G*, May–June	7	0.70	−113.9	7.5	0.015	44
	Plateau	Annual	4	0.91	−113.7	7.7	0.013	48
	Plateau	*G*, January–June	7	0.76	−110.8	10.6	0.003	200
	Linear	April–May	3	1.18	−107.5	13.9	0.001	1 044
	Plateau	*G*, April–May–June	7	0.90	−105.3	16.1	< 0.001	3 226
	Plateau	*G*, Annual	7	0.90	−105.1	16.3	< 0.001	3 530
	Linear	*G*, Growing season	5	1.09	−104.9	16.5	< 0.001	3 882
	Linear	*G*, April–May	5	1.18	−102.2	19.2	< 0.001	14 995
Wyoming	Plateau	April–May–June	4	1.51	−80.0	0	0.940	1
	Plateau	April–May	4	1.85	−74.0	6	0.045	21
	Plateau	*G*, April–May–June	7	1.48	−71.1	8.9	0.011	86
	Plateau	January–June	4	2.30	−67.4	12.6	0.002	554
	Plateau	May–June	4	2.33	−67.1	12.9	0.001	646
	Plateau	Growing season	4	2.45	−65.6	14.4	0.001	1 386
	Linear	*G*, January–June	5	2.49	−62.1	17.9	< 0.001	7 631
	Linear	*G*, April–May	5	2.64	−60.4	19.6	< 0.001	17 908
	Plateau	*G*, May–June	7	2.12	−60.4	19.6	< 0.001	18 288
	Linear	Annual	3	3.36	−58.8	21.2	< 0.001	40 946
	Plateau	*G*, Growing season	7	2.61	−54.1	25.9	< 0.001	421 258
	Linear	*G*, Annual	5	3.35	−53.2	26.8	< 0.001	659 344

[1]Plateau indicates the regression model was equation 4 or 6 described in the text.
[2]Predictor variables based on precipitation are described in Table 1 and G is an indicator variable for a grazing treatment.
[3]K is equal to the number of parameters in the regression model plus one because the variance of the population is an estimated parameter when calculating AIC for analyses based on least squares regression.

location indicates the best model. Our comparison of models indicates that the plateau model describes the relationship between precipitation and PSC better than a linear model; grazing does not influence this relationship; and precipitation during 2 or 3 mo in the spring is a superior predictor of PSC compared to annual or growing-season precipitation (Table 2).

We expected to find that the relationship between rescaled PSC and precipitation followed the typical relationship between plant productivity and resource levels—productivity increases with the resource (water) up to a plateau that begins when the resource in question is no longer the factor limiting productivity. Models with a plateau could be fit for most predictor variables for the North Dakota and Wyoming data sets, but could be fit for only one predictor variable for the Montana data set (Table 2). A plateau model had the lowest AIC for all locations and evidence ratios indicate the plateau model was much better than any linear model for a location. An evidence ratio for a model indicates how much more likely the best model is compared to that particular model. Smaller values indicate stronger support for a model (Anderson et al. 2000). The smallest evidence ratio for a top-ranked linear model was for Montana, yet in this case, the single model with the plateau is at least 17 times more likely than any of the linear models in the set.

Our results indicate that the relationship between production and precipitation is not influenced by grazing in these studies. The AIC criterion for selecting a model favors models with

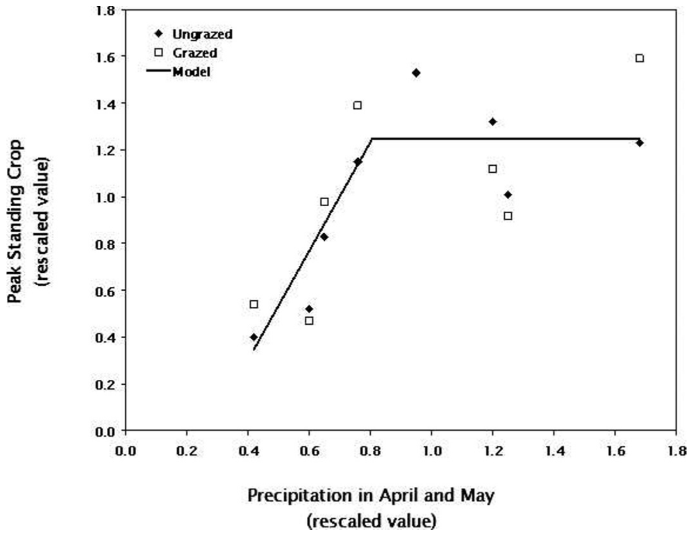

Figure 1. Model of the relationship between peak standing crop and total precipitation in April and May for Miles City, Montana. The regression model is equation 4 in the text.

fewer parameters (Anderson et al. 2000) and is therefore potentially biased against including grazing as a predictor in the model. However, the Akaike weights for models that include grazing as a predictor were very small compared to those that did not include grazing as a predictor (Table 2). The Akaike weight (w_i) for a model can be interpreted as the proportion of times that the model would be selected as "best" if the study were repeated. Larger values indicate more support for a model with a theoretical maximum value of 1 (the model would also be selected as the best model) and minimum value of 0 (the model would never be selected as best). The largest value of w_i for a model including grazing as a predictor variable was only 0.015 (North Dakota).

The best predictor variable was the total of April and May precipitation (April–May) for Montana, May and June precipitation (May–June) for North Dakota, and April, May, and June (April–May–June) precipitation for Wyoming (Table 2). Values of w_i for the best models among those we evaluated was 0.826 for Montana, 0.639 for North Dakota, and 0.940 for Wyoming. There was little support for all other models except for the model ranked second for North Dakota. This model was January through June (January–June) precipitation with w_i equal to 0.28. All other alternative models, for all the locations, had values of w_i less than 0.05 and were 20 times or more less likely than the best model for a location. June precipitation was an important component of the predictor for both Wyoming and North Dakota. The highest-ranked model without June precipitation for these locations was April–May for Wyoming. Although this model was ranked second, the evidence ratio was 21.

Spring precipitation was superior to annual or growing-season precipitation for predicting PSC in our study (Table 2). In fact, our results show very little evidence of a relationship between PSC and annual or growing-season precipitation in the data sets. The value of w_i for a model including annual or growing-season precipitation was less than 0.04 for North Dakota and was 0.001 or less for Montana and Wyoming.

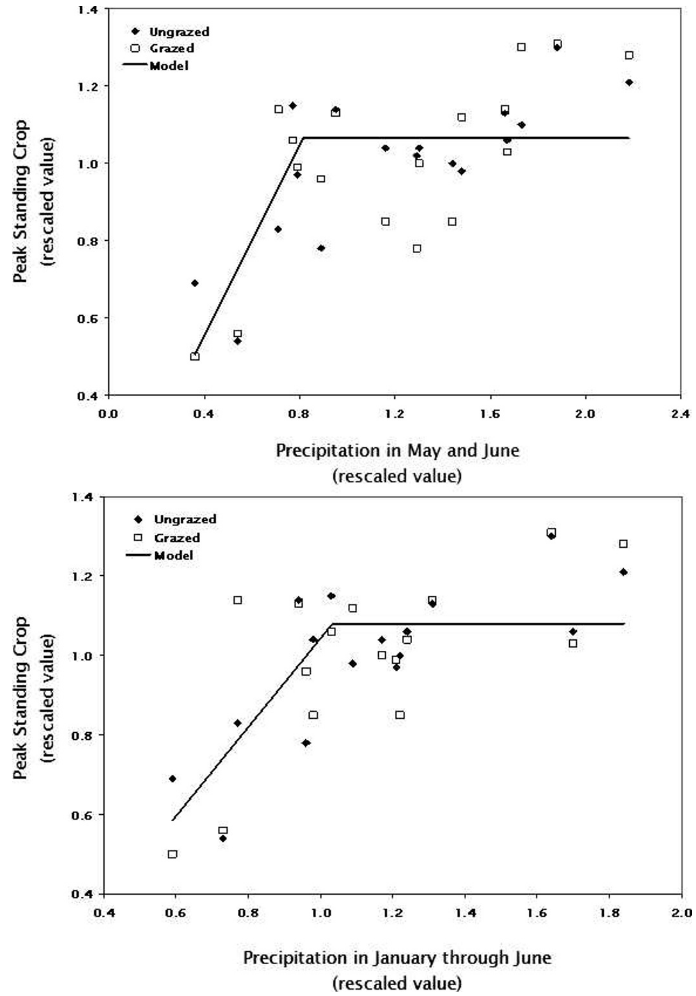

Figure 2. Model of the relationship between peak standing crop and total precipitation in May and June and January through June for Streeter, North Dakota. The regression model is equation 4 in the text.

Fit of the Best Models

The top-ranked models for Montana and Wyoming, and the two top-ranked models for North Dakota, are shown with the observed values in Figures 1, 2, and 3. Parameter estimates and measures of model fit are shown in Table 3. At least 50% of the variation in PSC, but no more than 70%, was explained by the top-ranked models (r^2). We also calculated the index of agreement (d) between the predicted and observed values because a model that systematically over- or underpredicts may have r^2 close to 1 (Krause et al. 2005). The value of d ranges from 0 to 1 with a value of 1 indicating perfect agreement between observed and predicted values. The value of d ranged from 0.80 (North Dakota, January–June) to 0.90 (Montana, April–May). The value of d for Wyoming was similar to that of Montana (April–May–June, 0.89).

We were most interested in the fit of the models where the amount of precipitation is predicted to limit forage production because our ultimate goal was a decision model to help decision makers determine if stocking rates should be reduced. This is the first linear segment of the model; it ends at the level of precipitation (P_{R_π}) at which the model reaches the plateau. The value of P_{R_π} was estimated to be 81% to

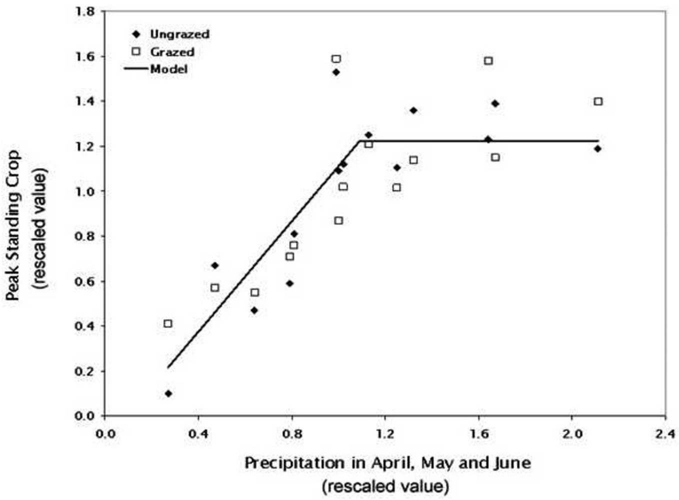

Figure 3. Model of the relationship between peak standing crop and total precipitation in April, May and June for Cheyenne, Wyoming. The regression model is equation 4 in the text.

109% of the long-term average precipitation. These values are consistent with our hypothesis that average precipitation results in average production. The models explained a greater proportion of variation in the data (62% to 79%), and there was greater agreement between predicted and observed values ($d = 0.88$ to 0.94), where precipitation was less than P_{R_π} than for the entire model. This is expected because water is not the factor limiting production where precipitation is greater than P_{R_π}. For North Dakota, the r^2 and d values of the linear segment were greater with May–June as the predictor variable compared to January–June, but January–June may still be an equivalent or better predictor. More low values of observed PSC were associated with levels of precipitation greater than P_{R_π} with May–June than with January–June (Fig. 2).

IMPLICATIONS

These results corroborate and inform our approach for developing a predictive model for a decision support tool to help ranchers with stocking and destocking decisions. The decision tool will require a model to predict the reduction of forage production due to spring drought. Ranking of models with AIC supports our intent to develop models to predict annual variation in forage production from annual variation in monthly spring precipitation as the models with spring precipitation as the predictor were better supported by the data than the models with annual or growing season as the predictor. Measures based on AIC identify the best among a set of models so a top-ranked model may merely be best among a set of poor models. However, we are encouraged because the top-ranked models explained 62% to 79% of the annual variation in forage production when precipitation was less than the long-term average. The predictive value of our final models must be evaluated with cross-validation, but a decision tool is valuable if the decision maker makes better decisions with than without the tool (Wilkerson et al. 2002). Ultimately, adoption of the decision tool will be the best measure of the predictive value of the decision tool.

Based on these results, we expect to develop linear models—models that are easy to implement in a spreadsheet—for the decision tool. Nonlinear models of the relationship between variation in production and forage production were better than linear models in this research, but the relationship was linear for levels of precipitation less than the long-term average. Development of appropriate predictive models based on spring precipitation will be complicated by the need to vary the spring months comprising the predictive variable by location, but it will not be necessary to develop a separate model for grazed and ungrazed prairie. June precipitation will likely be important for predicting variation in forage production at some locations. Decision makers who want to make predictions in early June or before will need to forecast June precipitation, or they may predict production with different levels of precipitation in June to see if their decision will depend on June precipitation. This use of the decision tool will be instinctive for decision makers because precipitation is expressed as proportional to the long-term average rather than as an absolute value.

ACKNOWLEDGMENTS

The authors thank Dr Mark West for supplying code for the regression analysis. The authors also wish to thank the scientists and staff from the three locations for access to their data. Specifically, Dr Justin Derner, US Department of Agriculture–Agricultural Research Service (USDA-ARS), Cheyenne, Wyoming; Dr Lance Vermeire, USDA-ARS, Miles City, Montana; and Dr Paul Nyren, North Dakota State University, Streeter, North Dakota.

Table 3. Best models for the relationship between forage production and precipitation for three locations. The parameters of the model (equation 4) are intercept (*a*), slope (*b*), plateau (π), and value of the predictor variable at which the plateau is reached ($P_{R\pi}$).

Location	Predictor variable	*a*	*b*	π	$P_{R\pi}$	Linear segment and plateau		Linear segment ($P_R \leq P_{R\pi}$)	
		Mean (SE)				r^2	*d*	r^2	*d*
Montana	April–May	−0.63 (0.41)	2.33 (0.67)	1.25 (0.09)	0.81 (0.11)	0.69	0.90	0.79	0.94
North Dakota	May–June	0.06 (0.19)	1.23 (0.30)	1.06 (0.03)	0.81 (0.08)	0.51	0.82	0.78	0.94
	January–June	−0.07 (0.24)	1.12 (0.28)	1.08 (0.04)	1.03 (0.08)	0.48	0.80	0.62	0.88
Wyoming	April–May–June	−0.12 (0.18)	1.23 (0.23)	1.22 (0.06)	1.09 (0.11)	0.66	0.89	0.74	0.92

LITERATURE CITED

Anderson, D. R., K. P. Burnham, and W. L. Thompson. 2000. Null hypothesis testing: problems, prevalence, and an alternative. *Journal of Wildlife Management* 64(4):912–923.

Bartholomew, P. W., and R. D. Williams. 2005. Cool-season grass development response to accumulated temperature under a range of temperature regimes. *Crop Science* 45:529–534.

Biondini, M. E., B. D. Patton, and P. E. Nyren. 1998. Grazing intensity and ecosystem processes in a northern mixed-grass prairie, USA. *Ecological Applications* 8(2):469–479.

Briggs, J. M., and A. K. Knapp. 1995. Interannual variability in primary production in tallgrass prairie: climate, soil moisture, topographic position, and fire as determinants of aboveground biomass. *American Journal of Botany* 82(8):1024–1030.

Currie, P. O., and G. Peterson. 1966. Using growing-season precipitation to predict crested wheatgrass yields. *Journal of Range Management* 19(5):284–288.

Dahl, B. E. 1963. Soil moisture as predictive index of forage yield for the sandhills range type. *Journal of Range Management* 16(3):128–132.

Derner, J. D., and R. H. Hart. 2007. Grazing-induced modifications to PSC in northern mixed-grass prairie. *Rangeland Ecology & Management* 60(3):270–275.

Eneboe, E. J., B. F. Sowell, R. K. Heitschmidt, M. G. Karl, and M. R. Kaferkamp. 2002. Drought and grazing: IV. Blue grama and western wheatgrass. *Journal of Range Management* 55(2):197–203.

Epstein, H. E., W. K. Lauenroth, I. C. Burke, and D. P. Coffin. 1996. Ecological responses of dominant grasses along two climatic gradients in the Great Plains of the United States. *Journal of Vegetation Science* 7(6):777–788.

Frank, A. B., S. Bittman, and D. A. Johnson. 1996. Water relations of cool-season grasses. *Agronomy Monograph* 34:127–164.

Gillen, R. L., and P. L. Sims. 2006. Stocking rate and weather impacts on sand sagebrush and grasses: a 20-year record. *Rangeland Ecology & Management* 59:145–152.

Heitschmidt, R. K., K. D. Klement, and M. R. Haferkamp. 2005. Interactive effects of drought and grazing on Northern Great Plains rangelands. *Rangeland Ecology & Management* 58:11–19.

Kendall, M. G., and A. Stuart. 1969. The advanced theory of statistics. 3rd ed. New York, NY, USA: Hafner Publishing Company. 439 p.

Krause, P., D. P. Boyle, and F. Bäse. 2005. Comparison of different efficient criteria for hydrological model assessment. *Advances in Geosciences* 5:80–97.

Lauenroth, W. K., and O. E. Sala. 1992. Long-term forage production of North American shortgrass steppe. *Ecological Application* 2(4):397–403.

Lauenroth, W. K., and W. C. Whitman. 1977. Dynamics of dry matter production in a mixed-grass prairie in western North Dakota. *Oecologia* 27:339–351.

Marques da Silva, J. R., J. O. Peca, J. M. Serrano, M. J. de Carvalho, and P. M. Palma. 2008. Evaluation of spatial and temporal variability of pasture based on topography and the quality of the rainy season. *Precision Agricultural* 9:209–229.

[NDAWN] North Dakota Agricultural Weather Network. 2008. NDAWN Center. Available at: http://ndawn.ndsu.nodak.edu. Accessed 10 February 2009.

Oesterheld, M., J. Loreti, M. Semmartin, S. Semmartin, and E. Osvaldo. 2001. Inter-annual variation in primary production of a semi-arid grassland related to previous year-production. *Journal of Vegetation Science* 12:137–142.

Radosevich, S. R., and J. S. Holt. 1984. Weed ecology: implications for vegetation management. New York, NY, USA: Wiley. 265 p.

Richards, S. 2005. Testing ecological theory using the information-theoretic approach: examples and cautionary results. *Ecology* 86:2805–2814.

Schwinning, S., B. I. Starr, and J. R. Ehleringer. 2005. Summer and winter drought in a cold desert ecosystem (Colorado Plateau) part II: effects on plant carbon assimilation and growth. *Journal of Arid Environments* 61:61–78.

Sims, P. L., and J. S. Singh. 1978. The structure and function of ten western North American grasslands: II intra-seasonal dynamics in primary producer compartments. *Journal of Ecology* 66(2):547–572.

Smart, A. J., B. H. Dunn, P. S. Johnson, L. Xu, and R. N. Gates. 2007. Using weather data to explain herbage yield on three Great Plains plant communities. *Rangeland Ecology & Management* 60:146–153.

Smoliak, S. 1986. Influence of climatic conditions on production of Stipa-Bouteloua prairie over a 5-year period. *Journal of Range Management* 39(2): 100–103.

Vallentine, J. F. 2001. Grazing management. 2nd edition. San Diego, CA, USA: Academic Press. 659 p.

Willmott, C. J. 1981. On the validation of models. *Physical Geography* 2:184–194.

Wilkerson, G., L. Wiles, and A. Bennett. 2002. Weed management decision models: pitfalls, perceptions, and possibilities of the economic threshold approach. *Weed Science* 50:411–424.

[WRCC] Western Regional Climate Center. 2008. Western Regional Climate Center. Available at: http://www.wrcc.dri.edu. Accessed 10 February 2009.