Published December 5, 2014

Using a Model and Forecasted Weather to Predict Forage and Livestock Production for Making Stocking Decisions in the Coming Growing Season

Quan X. Fang,* L.R. Ahuja, Allan A. Andales, and Justin D. Derner

Abstract

Forecasting peak standing crop (PSC) for the coming grazing season can help ranchers make appropriate stocking decisions to reduce enterprise risks. Previously developed PSC predictors were based on short-term experimental data (<15 yr) and limited stocking rates (SR) without including the effect of SR on PSC explicitly. Here we used long-term (30 yr) measured data of PSC and steer weight gain (SWG), extended with the help of a model for SR effect, to develop multiple-variable regression functions for predicting PSC and SWG across a wide range of SR (0.2–1.32 steers ha^{-1} for summer grazing season, June to mid-October) on a loam soil in a northern mixed-grass prairie. April to June rainfall was the primary weather variable influencing PSC (R^2 = 0.45); inclusion of SR and soil water content on 1 April improved the accuracy in predicting PSC (R^2 = 0.64). Combining the response of PSC to SR and the response of SWG to both PSC and SR enables ranchers to explore tradeoffs between economic net return and environmental impact (land conservation) as influenced by SR and weather variations. The result was further extended from the loam soil at the experimental site to the other two soil types (loam sandy and clay loam soils) by using a simple soil influence factor. A simple spreadsheet-based decision support tool can be developed to facilitate stocking decisions by ranchers in a northern mixed-grass prairie to adaptively manage rangelands in an effort to increase economic net return and reduce land degradation associated with high weather variability and SR levels.

Abbreviations: DC, Drought Calculator; HPGRS, High Plains Grasslands Research Station; HPPSC, peak standing crop; GPFARM, Great Plains Framework for Agricultural Resource Management; PSC, peak standing crop; SR, stocking rate; SWG, steer weight gain; TDN, total intake digestible nutrient.

Quan X. Fang Agronomy College, Qingdao Agricultural University, Changcheng Road 700, Chengyang District, Qingdao, Shandong, China, 266108. *Corresponding author (fangqx@igsnrr.ac.cn)

L.R. Ahuja, USDA-ARS-NPA-ASRU 2150 Centre Ave., Bldg. D, Ste. 200 Fort Collins, CO, 80526 (laj.ahuja@ars.usda.gov)

A.A. Andales, Department of Soil and Crop Sciences, Colorado State University, 1170 Campus Delivery, Fort Collins, CO 80523-1170 (Allan.Andales@colostate.edu).

J.D. Derner, USDA-ARS, High Plains Grasslands Research Station, 8408 Hildreth Road, Cheyenne, WY 82009-8899 (Justin.Derner@ars.usda.gov)

doi:10.2134/advagricsystmodel5.c7

Copyright © 2014. ASA, CSSA, SSSA, 5585 Guilford Rd., Madison, WI 53711-5801, USA.
Practical Applications of Agricultural System Models to Optimize the Use of Limited Water
Lajpat R. Ahuja, Liwang Ma, and Robert J. Lascano, Editors
Advances in Agricultural Systems Modeling, Volume 5. Lajpat R. Ahuja, Series Editor

USDA-NRCS

Ranchers need to make stocking decisions for the upcoming grazing season before the initiation of forage growth. Weather variability (e.g., rainfall) is the most important factor influencing forage production in semi-arid areas (e.g., Milchunas et al., 1994; Biondini et al., 1998; Derner and Hart, 2007). Relationships between forage production and seasonal or spring (April–June) precipitation have been well established for many rangelands, such as the northern mixed-grass prairie of the United States (Currie and Peterson, 1966; Lauenroth and Sala 1992; Derner and Hart, 2007; Derner et al., 2008b, Smart et al., 2007; Wiles et al., 2011) and the central grassland region of the United States (Sala et al., 1988). Forecasting of spring rainfall, PSC, and cattle weight gain before the grazing season would facilitate better decision-making for reducing enterprise risk for ranchers.

In addition to spring precipitation, soil water content at the beginning of the growing season increases the robustness of predictions of PSC (Briggs and Knapp, 1995; Andales et al., 2006; Torell et al., 2011). Dahl (1963) found that soil water and depth of moist soil on 15 April were useful indices for predicting grass production by early August in rangelands of eastern Colorado. Torell et al. (2011) used measured soil water to improve predictions of forage production in rangelands of New Mexico. Andales et al. (2006) used the Great Plains Framework for Agricultural Resource Management (GPFARM)-Range model with different initial soil water levels in early April to produce improved response functions of PSC to spring precipitation in the northern mixed-grass prairie.

Stocking decisions by ranchers are dependent on PSC (Wiles et al., 2011; Dunn et al., 2013) as forage availability limits cattle intake and weight gains (e.g., Bement 1969; Redmon et al., 1995; Poppi, 1996). The aforementioned studies, however, did not account for the effect of SR on PSC and cattle weight gain. Recent studies have showed that high SR can reduce PSC, such as in the northern mixed-grass prairie of the United States (Derner and Hart, 2007), and the response of PSC or livestock weight gain to weather variables differs with different grazing levels (Reeves et al., 2013a, 2013b, 2014). In this context, integrating the effect of SR and weather variables on PSC can potentially improve the predictions of PSC compared with predictions based on the weather variables alone, thus improve stocking decisions. Additionally, the cattle weight gains were not quantified as functions of PSC and SR in the previous stocking decision support tools. Thus, this precludes economic risk analyses at the different SR levels. Additionally, land degradation due to overgrazing with high SR should also be accounted for in making SR decisions (Smart et al., 2010).

In this study, we used PSC and SWG data from a long-term (1982–2012) experiment to create model simulated data sets with much higher (50–150%) SR levels than the experimental grazing levels (Derner and Hart 2007; Derner et al., 2008a). We then used the extended dataset to (i) obtain better PSC predictions as a function of spring rainfall, soil water before grazing seasons, and SR and (ii) combine the SR effects on SWG and land degradation across different soil types in the PSC predictor and help ranchers to make better SR decisions considering both net return and land conservations.

Materials and Methods

Peak Standing Crop and Steer Weight Gain from Long-Term Field Experiments

Peak standing crop was measured annually in mid to late July from a long-term grazing experiment on the semiarid northern mixed-grass prairie at the High Plains Grasslands Research Station (HPGRS) in Cheyenne, WY (41°11′ N, 104°53′ W) (Derner and Hart, 2007; Derner et al., 2008a). Mean annual precipitation at the site is 381 mm with peaks of precipitation in April, May, and June. The soils are medium textured and well drained, largely composed of Albinas, Asclon, and Altvan loams and Cascajo gravelly loam (Stevenson et al., 1984).

Season-long (June to mid-October. 4.5 mo), continuous grazing treatments were initiated in 1982 with the following three SR levels: light [8 steers per 40 ha (0.20 steer ha^{-1}), about 35% below the USDA–NRCS recommended rate], moderate [8 steers per 24 ha (0.33 steer ha^{-1}), the USDA–NRCS recommended rate], and heavy (8 steers per 18 ha (0.44 steer ha^{-1}), 33% above the USDA–NRCS recommended rate) (Hart et al., 1988). Yearling steers were used as grazing animals, and each steer was weighed before and after the season and all experimental procedures were approved by the HPGRS Animal Care and Use Committee.

Peak Standing Crop and Steer Weight Gain from GPFARM-Range Model Simulations

The forage and cattle modules of GPFARM-Range are simplified versions of the Simulating Production and Utilization of Rangeland (SPUR) model (Hanson et al., 1988, 1992). Model details, including functions and equations for both the forage and cattle modules, have been published previously (Andales et al., 2005, 2006). Recently, the GPFARM-Range model was improved by considering the SR effect on PSC and steer weight and the revised model showed a reasonable response of

PSC and SWG to different grazing levels across long-term weather conditions as shown in Fig. 7–1 (Fang et al., 2014).

The improved model was used to simulate PSC and SWG for four SR greater than the above experimental values, in addition to the three experimental SR treatments, from 1982 to 2012. The six higher SR levels were 50 to 150% greater than the highest experimental SR of 0.44 steer ha^{-1}, including (i) 0.66 steer ha^{-1} (50% greater), (ii) 0.88 steer ha^{-1} (100% greater), and (iii) 1.10 steer ha^{-1} (150% greater). See Fang et al. (2014) for more detailed information.

Multiple Regression Analysis and Economic Analysis

On the basis of previous studies on the relationships between PSC and weather variables (e.g., Eneboe et al., 2002; Derner and Hart, 2007; Patton et al., 2007; Smart et al., 2007; Torell et al., 2011; Wiles et al., 2011), the weather variables (precipitation), SR, and soil water on 1 April were used for predicting both experimentally

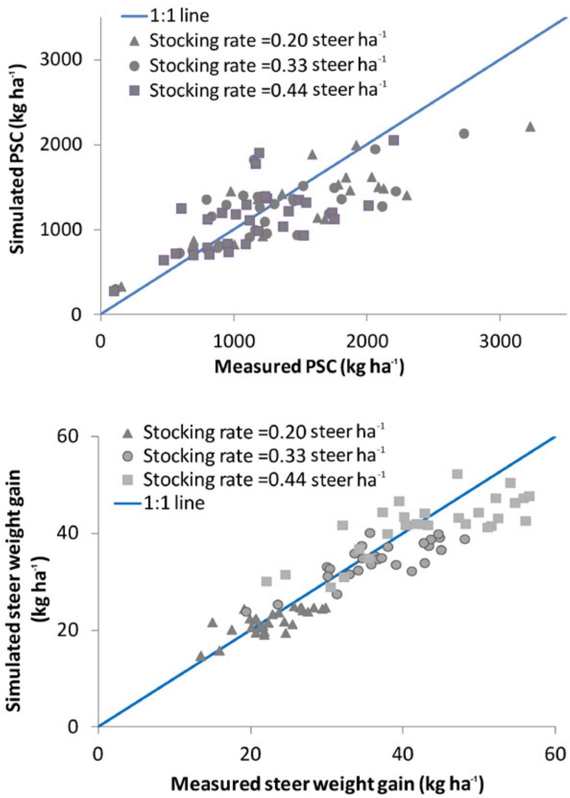

Fig. 7–1. GPFARM-Range model evaluations on simulating peak standing crop (PSC) and steer weight gain under the three stocking rate experimental treatments from 1982 to 2012 (detailed information can be found Fang et al., 2014).

observed PSC data and GPFARM model simulated PSC. Multivariate stepwise regression was used to evaluate the contribution of each of the above variables for predicting PSC. The contribution of precipitation was evaluated on a trimonthly basis from January to September according to the abovementioned studies in the region. Besides PSC, the dependent variables of harvest efficiency and SWG were also predicted on the basis of PSC and SR by using the multivariate stepwise regression method, where interactions between PSC and SR were included. The harvest efficiency, defined as the ratio of forage intake to forage production (Smart et al., 2010), reflects the grazing pressure and can be used as an important indicator for SR decisions (Galt et al., 2000). A stepwise procedure of RSREG (Response Surface Regression) in SAS (Statistical Analysis System) (Freund and Littell, 1991) was used for the variable selections ($P < 0.01$), which combines forward selection and backward elimination steps for variable selection.

Because the model does not simulate the carrying costs (such as supplement cost, salt, implants, and transportation) of a grazing enterprise, a simple method was used to estimate the economic profit based on previous studies in the region (Hart et al., 1988; Manley et al., 1997). The purchase price in March and selling price in October for the simulation period (1982–2012) in the United States were obtained from USDA–NASS (2014), and we estimated carrying costs at $US60 per steer. Predicted SWG values from the different SR levels were used to estimate economic net returns each year.

Extending the Regression Equations to Other Soils

We simulated PSC and SWG using the seven SR levels for the other two different soil types (loam sandy soil and clay loam soil) from 1982 to 2012. These simulated data were used to estimate effects of soil types on the responses of PSC and SWG to SR under the same climate conditions. To keep this tool simple, we used a simple soil factor to extend the regression equation from a loam soil (experimental site soil) to the other two soil types (clay loam soil and loam sandy soils). The soil factor was obtained based on the relationships of PSC or SWG from 1982 to 2012 between the different soils.

Results and Discussion

Identifying the Influential Factors for Yearly Variability of Peak Standing Crop or Steer Weight Gain

For predicting both observed and model simulated PSC, the trimonthly rainfall amounts from January to March or from July to September were not significant for predicting PSC across the different SR levels (Table 7–1). The April to June

Table 7–1. The most influential variables selected ($P < 0.01$) with partial R^2 values based on the multivariate regressions for both observed peak standing crop (MPSC) or steer weight gain (OSWG) and GPFARM-Range model predicted PSC (SPSC) and weight gain (SSWG) from 1982 to 2012 under different stocking rates (steer ha^{-1}) for a 4.5-mo grazing season.†

	Stocking rate for experiment				Stocking rate for long-term simulations							
Variable	0.20	0.33	0.44	Total	0.20	0.33	0.44	0.66	0.88	1.10	1.32	Total
	steer ha^{-1}				steer ha^{-1}							
	MPSC				SPSC							
$Rain_{123}$	no	no	no	no	no	no	no	no	no	no	no	no
$Rain_{456}$	0.39	0.43	0.43	0.38	0.64	0.57	0.54	0.47	0.50	0.51	0.52	0.45
$Rain_{789}$	no	no	no	no	no	no	no	no	no	no	no	no
SW	0.03	0.05	0.02	0.03	0.05	0.05	0.07	0.08	0.06	0.04	0.06	0.05
SR	–	–	–	0.08	–	–	–	–	–	–		0.14
	MSWG				SSWG							
PSC	no	no	no	no	no	no	no	no	0.79	0.74	0.68	0.04
TDN	–	–	–	–	0.87	0.85	0.81	0.74	0.09	0.08	0.08	0.37
SR	–	–	–	0.59	–	–	–	–	–	–	–	0.15

† Climatic variables: $rain_{123}$, total rainfall (mm) from January to March; $rain_{456}$, total rainfall (mm) from April to June; $rain_{789}$, total rainfall (mm) from July to September. Other variables: SW, soil water content on 1 April; SR, stocking rate; PSC, peak standing crop; TDN, total intake digestible nutrient. The word "no" means this variable was not included at $P < 0.01$ level, and "–" means this variable was not used for regression analysis.

(spring) rainfall was identified as the most important factor ($P < 0.01$, partial R^2 from 0.39 to 0.64) to both observed PSC and model simulated PSC, respectively (Table 7–1). Similar results were found with field experiments in this rangeland ecosystem (Derner and Hart, 2007; Smart et al., 2007; Derner et al., 2008b; Wiles et al., 2011). The effect of SR on PSC was significant ($P < 0.01$) but with a partial R^2 of 0.08 (observed PSC) and 0.15 (simulated PSC) (Table 7–1). Soil water affected PSC for both experimental data and model simulation results, agreeing with prior findings (Andales et al., 2006; Torell et al., 2011). Simulated soil water content on 1 April influenced PSC ($P < 0.01$) (Table 7–1). A significant positive relationship was obtained between the GPFARM simulated soil water content on 1 April with the observed PSC ($R^2 = 0.08$, $n = 93$; $P < 0.001$) or the simulated PSC ($R^2 = 0.14$, $n = 279$; $P < 0.001$) across the SR levels. This result showcases that including soil water content on 1 April improves the PSC predictions over those based on spring rainfall only. We also found a significant ($P < 0.001$) linear relationship between soil water content on 1 April and the precipitation in March of the current year and December of the previous year, which explained 41 and 18% of the variation in soil water content on 1 April across seasons, respectively (Eq. [4] in Table 7–2), and other variables of rainfall in January, October, and November of the previous year were also significant but explained less variations in soil water content on 1 April. This regression equation based on previous precipitation can be used to estimate

Table 7–2. Regression equations for GPFARM-Range simulated peak standing crop when using rainfall, stocking rate, and GPFARM-Range simulated soil water (0–50 cm) on 1 April and for GPFARM-Range model predicted forage harvest efficiency and steer weight gain using peak standing crop and stocking rate (Fig. 7–4).†

Number	Variable	Equations	Statistic results
[1]	PSC	$4.16 \times rain_{456} + 358.41$	RMSE = 358, $R^2 = 0.45$, $N = 217$
[2]	PSC	$620.36 + 4.16 \times rain_{456} - 370.04 \times SR$	RMSE = 246, $R^2 = 0.588$, $N = 217$
[3]	PSC	$-370.69 + 3.85 \times rain_{456} - 363.17 \times SR + 5800.05 \times SWP$	RMSE = 231, $R^2 = 0.637$, $N = 217$
[4]	SWP	$0.14483 - 5.61e{-4} \times rain_1 + 4.14e{-4} \times rain_3 + 5.79e{-4} \times prain_{12} + 2.55e{-4} \times prain_{10} + 2.71e{-4} \times prain_{11}$	RMSE = 0.0089, $R^2 = 0.647$, $N = 217$
[5]	HE	$0.47820 - 0.00042531 \times PSC + 0.94588 \times SR$	RMSE = 0.17, $R^2 = 0.87$, $N = 217$
[8]	HE	$0.00831 + 1.63 \times SR - 6.71e{-4} \times SR \times PSC$	RMSE = 0.15, $R^2 = 0.91$, $N = 217$
[9]	SWG	$-16.54 + 0.04 \times PSC + 41.15 \times SR - 1.95e{-5} \times PSC^2 - 45.60 \times SR^2 + 0.06 \times SR \times PSC$	RMSE = 9.1, $R^2 = 0.84$, $N = 217$

† Climatic variables: $rain_{456}$, rainfall from April to June; $rain_1$, rainfall in January; $rain_3$, rainfall in March; $prain_{10}$, monthly rainfall during October in the previous year; $prain_{11}$, monthly rainfall during November in the previous year; $prain_{12}$, monthly rainfall during December in the previous year. Other variables: PSC, peak standing crop (kg ha^{-1}); SR, stocking rate (steer ha^{-1}); SWP, GPFARM simulated soil water (cm^3 cm^{-3}); HE, harvest efficiency; SWG, steer weight gain (kg ha^{-1}).

soil water content on 1 April (before forage growth begins) when the observed value is not available.

Peak standing crop was not identified as a significant ($P > 0.19$) influential factor for predicting observed SWG for the experimental SR levels (0.20–0.44 steer ha^{-1}) (Table 7–1), and similar results were also obtained for the simulated SWG. Under higher SR levels from 0.88 to 1.32 steer ha^{-1}, however, PSC became the most limiting factor for the simulated SWG with a partial R^2 of 0.79 to 0.68. Considering all the SR treatments, SR was the most important factor to limiting SWG with a partial R^2 of 0.59, and this agrees with prior research (Reeves et al., 2013b). For the simulated SWG data, however, PSC, total intake digestible nutrient (TDN) and SR were all significant in predicting SWG, and a linear relationship between PSC and TDN was also found ($R^2 = 0.50$) for these simulated data.

Improving Peak Standing Crop Predictions by Including Soil Water and Stocking Rate

Extending the PSC predictions to a wider range of weather and grazing conditions is needed to assist in decision-making for ranchers. The PSC predictions from the regression equations based on the spring rainfall (Fig. 7–2a), spring rainfall plus SR (Fig. 7–2b), or spring rainfall plus SR and predicted soil water on 1

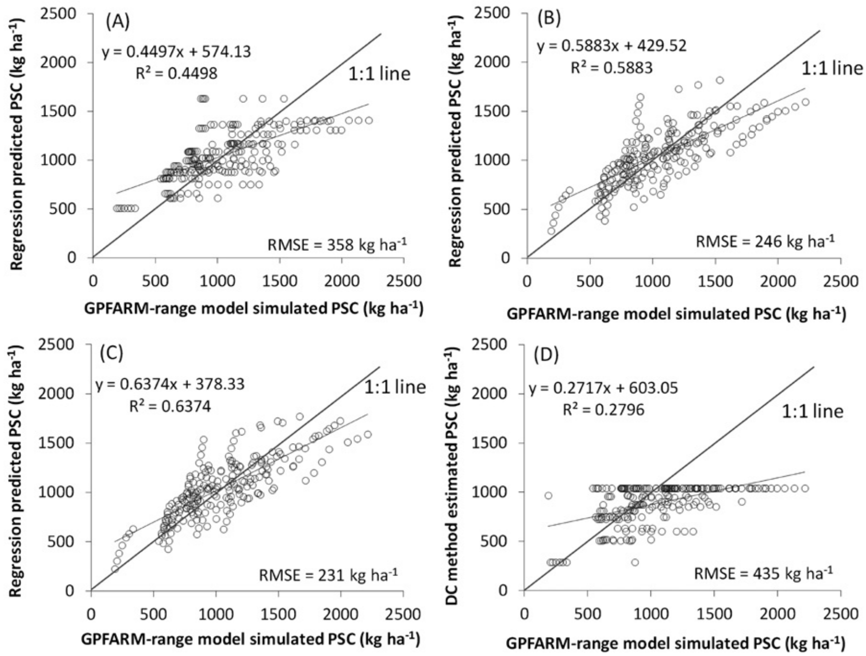

Fig. 7–2. Comparing the performances in predicting peak standing crop (PSC) for the developed regression equations based on (a) April to June rainfall (Eq. [1] in Table 7–2), (b) April to June rainfall and stocking rate (Eq. [2] in Table 7–2), (c) April to June rainfall, stocking rate, and soil water content on 1 April (Eq. [3] in Table 7–2), and (d) the Drought Calculator (DC method [Dunn et al., 2013]), with PSC values simulated by the GPFARM-Range model. The up-bound in estimated PSC by the DC method (d) is the average simulated PSC level from 1982 to 2012.

April (Fig. 7–2c) were compared with the earlier Drought Calculator (DC) method (Dunn et al., 2013) (Fig. 7–2d). As expected, using variables of spring rainfall and SR produced better PSC predictions (RMSE = 246 kg ha^{-1}; R^2 = 0.59) than the PSC predictions using spring rainfall only (RMSE = 358 kg ha^{-1}; R^2 = 0.45). Further, by including soil water on 1 April, PSC predictions were improved with an RMSE value of 231 kg ha^{-1} and R^2 of 0.64. For the DC method (Dunn et al., 2013), a better performance in predicting PSC was obtained when the PSC level was below 1000 kg ha^{-1} because of the drought stresses, and obvious under-predictions occurred when PSC level was higher than 1000 kg ha^{-1} when there was no or little drought stress (Fig. 7–2d). The regression equations improved the predictions, especially at high PSC level with little or no drought stresses, compared with the predictions from DC method (RMSE = 435 kg ha^{-1}).

Next, we compared predicted PSC (regression equations in Table 7–2 and DC method) and measured data under the three SR levels (Fig. 7–3). Both regression equations and DC methods predicted PSC well when measured PSC

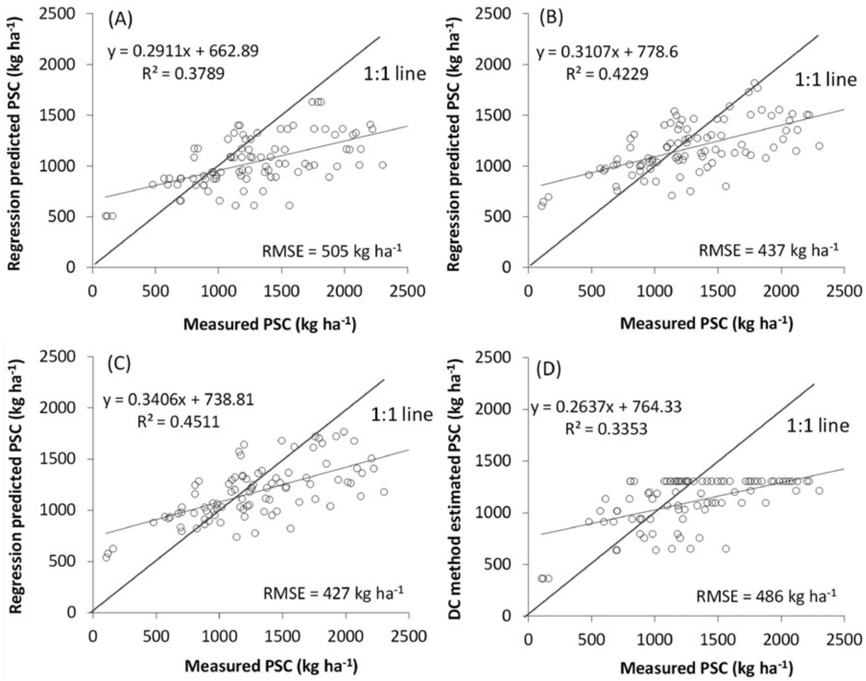

Fig. 7–3. Comparing the performances in predicting peak standing crop (PSC) for the developed regression equations based on (a) April to June rainfall (Eq. [1] in Table 7–2), (b) April to June rainfall and stocking rate (Eq. [2] in Table 7–2), (c) April to June rainfall, stocking rate, and soil water content on 1 April (Eq. [3] in Table 7–2), and (d) the Drought Calculator (DC method [Dunn et al., 2013]), with the experimental measured PSC. The up-bound in estimated PSC by the DC method (d) is the average simulated PSC level from 1982 to 2012.

was below average levels, but under-predicted PSC occurred when PSC values were above average. The regression equation based on GPFARM simulated PSC under-predicted PSC because of the GPFARM under-simulated PSC compared with measured data (Fig. 7–1). Slightly better predictions of PSC were obtained from the regression equation than from the DC method with lower RMSE values (Fig. 7–3). The inclusion of the SR effect on PSC in the regression equations was demonstrated from a field experiment study (Derner and Hart, 2007). The developed regression equations produced a comparable performance in predicting PSC to the DC method and can be applied to predict PSC across a wider range of SR and weather conditions.

Extending to Forecast Harvest Efficiency and Steer Weight Gain Using Stocking Rate and Peak Standing Crop

To assist ranchers with stocking decisions, other indicators, such as forage harvest efficiency (total forage intake/PSC as defined by Smart et al. [2010]) and SWG, are needed to account for SR effect on economic profits (SWG) and environmental impacts (land conservation). On the basis of the long-term simulations with a wider range of SR levels, the regression equations for simulated harvest efficiency or SWG based on the variables of PSC and SR are presented in Table 7–2. For predicting SWG or harvest efficiency, interactions between PSC and SR were significant ($P < 0.01$) and were included in the regression equations. This result was consistent with previous experimental studies (Derner and Hart, 2007; Smart et al., 2010). These regression equations showed good performances in predicting forage harvest efficiency (Fig. 7–4a) and SWG (Fig. 7–4b) across these seasons, with RMSE values of 0.18 and 9.3 kg ha^{-1}, respectively, which can help ranchers predict harvest efficiency and SWG based on the PSC and SR levels and make better SR decisions based on the SR effects on land degradation (low PSC level associated with high SR levels) and economic net return.

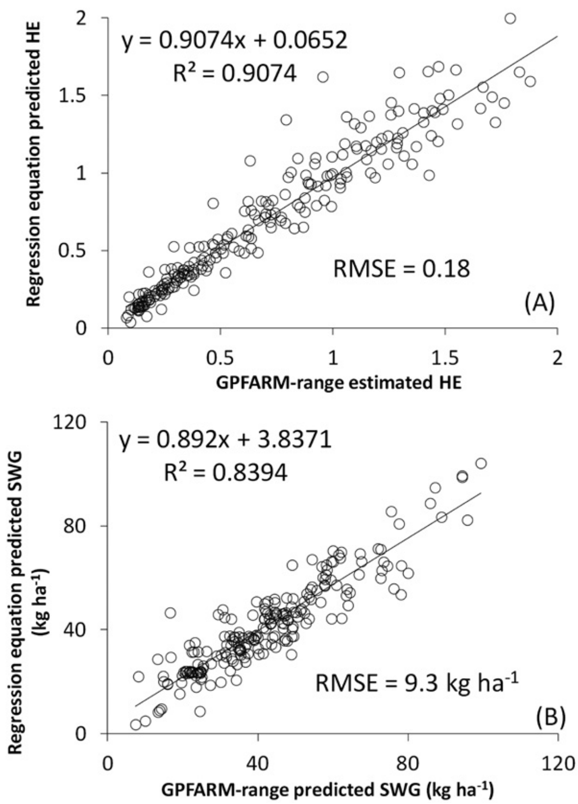

Fig. 7–4. Comparisons between regression equation predicted forage harvest efficiency (HE, Eq. [5] in Table 7–2) and steer weight gain (SWG, kg ha^{-1}, Eq. [6] in Table 7–2) with GPFARM-Range model simulated data from 1982 to 2012.

The regression equation developed for SWG in Table 7–2 (Eq. [9]) is based on simulated data for all seven SR and thus includes the effect of PSC at all SR levels. On the other hand, there was no significant relationship between SWG and PSC at the three lower SR used in the experiment for both measured and simulated data (Table 7–1), indicating that the PSC was not a limiting factor to SWG under the low SR conditions. We explored if Eq. [9] supports this effect. As shown in Fig. 7–5a, the response of the predicted SWG to different levels of PSC by the regression equation, Eq. [9], was small and apparently insignificant under the low SR level (0.20 steer ha^{-1}) compared with the high SR level (0.60 steer ha^{-1}). This result was consistent with the measured and simulated data, where no significant influence of PSC on SWG at the low SR levels was found (Table 7–1). We further compared the predicted SWG from the regression equation, Eq. [9], based on the simulated data and another equation based only on experimental measured data as a function of SR levels (Fig. 7–5b). Both equations predicted very similar SWG at the low SR level. This result indicated that the regression equation based on the simulated data (Eq. [9] in Table 7–2) was effective in predicting SWG even under the low SR levels. While at higher SR levels, the regression equation based the experimental data tended to oversimulate SWG because it did not consider the reductions in PSC caused by high SR. Therefore, the regression equation based on the simulated data with a wider range of SR was selected since it reflects the experimental data.

Extending the Regression Equations to Other Soil Types

We first compared the GPFARM simulated PSC and SWG for the different SR levels for the three soils, for example, loam soil (experimental field soil), loam sandy soil, and clay loam soil, as shown in Fig. 7–6. For the predicted PSC from

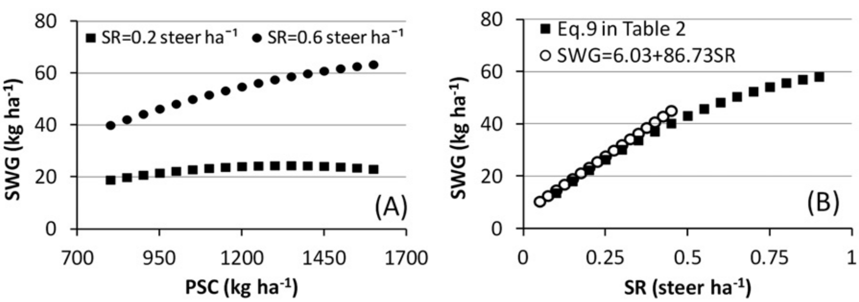

Fig. 7–5. Comparisons of (a) the response of steer weight gain (SWG) with peak standing crop (PSC) between the low (0.20 steer ha^{-1}) and high (0.60 steer ha^{-1}) stocking rates (SR) based on the regression Eq. [9] in Table 7–2 and (b) the response of SWG to SR between the regression equation based on the simulated data (Eq. [9] in Table 7–2) and the experimental data (SWG = 6.03 + 86.73 × SR based on Table 7–1).

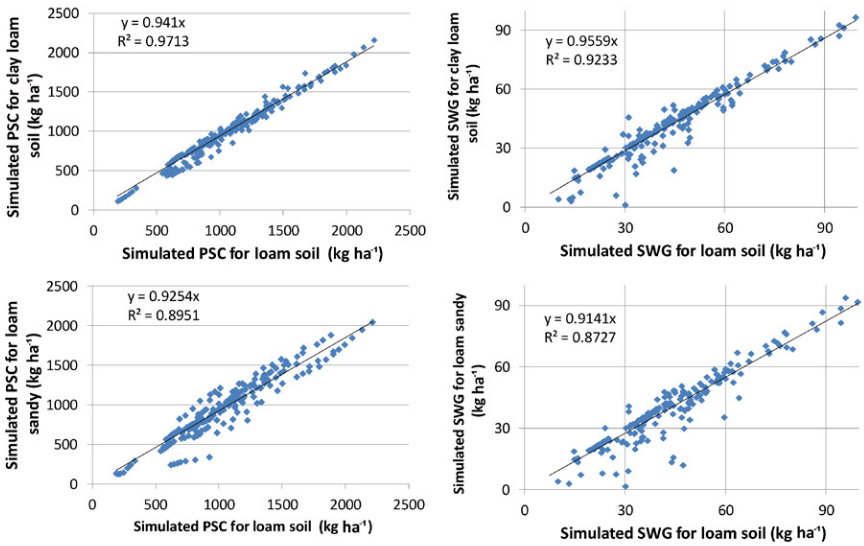

Fig. 7–6. Comparisons of GPFARM-Range simulated long-term (1982–2012) seasonal peak standing crop (PSC) and steer weight gain (SWG) on the loam soil (experimental field soil) to the clay loam or loam sandy soils.

1982 to 2012, strong linear relationships between loam and clay loam soils or between loam and loam sandy soils were found with R^2 values of 0.97 or 0.90, respectively. The long-term predicted average PSC were slightly lower for clay loam soil (slope = 0.94) and loam sandy (slope = 0.93) soils than for loam soils. The SR level showed little or no effect on abovementioned relationships between these different soils. The abovementioned relationships in PSC among these different soil types suggested that the PSC is lower for loam sandy and clay loam soils than for loam soil, and a simple soil influence factor on PSC (the slopes for the relationships) can be used to extend the regression equation of PSC for loam soil to clay loam soil (slope = 0.94) and loam sand soil (slope = 0.93). Such an extension method was very simple and was easier for ranchers to adopt.

For the predicted SWG from 1982 to 2012, linear relationships between loam and clay loam soils or between loam and loam sandy soils were also found with R^2 values of 0.92 or 0.87, respectively. The long-term predicted SWG was slightly lower for clay loam (slope = 0.96) or loam sandy (slope = 0.91) soils than for loam soils, which suggested that different soil factors should be used for the different SR levels. Specifically, when SR levels were below 0.88 steer ha^{-1}, the slopes for the SWG relationship between loam and loam sandy soils are similar (0.98–0.97), and one soil influence factor of 0.97 was used for the SR levels. When SR levels were between 1.1 and 1.32 steer ha^{-1}, the soil influence factor of 0.94 was used.

Similarly, when extending the results from loam soil to loam sandy soil, the soil influence factor of 0.95 and 0.90 was used for the SR levels below 0.88 steer ha^{-1} and above 0.88 steer ha^{-1}, respectively (Table 7–3).The GPFARM-Range predicted PSC or SWG and the estimated data from equations based on above soil influence factor were very close with a strong linear relationship (slope values between 0.98 and 1, and R^2 values between 0.87 and 0.97). This suggests that it was reasonable to extend the regression equations from the loam soil to other soils (such as clay loam and loam sandy soils) using the soil influence factor.

Better Stocking Decisions Based on Peak Standing Crop and Steer Weight Gain and Economic Analysis

On the basis of the regression equations for PSC and SWG (Table 7–2), ranchers can forecast their PSC and SWG before the grazing season, with the National Weather Service forecast of rainfall from April to June and soil water on 1 April (measured or estimated from previous rainfall based on regression Eq. [4] in Table 7–2). The forage harvest efficiency can also be predicted on the basis of the predicted PSC and SR levels (Eq. [5] in Table 7–2). These regression equations can be developed into a spreadsheet-based decision support tool and help ranchers explore the effects of SR and weather on PSC and SWG.

In Fig. 7–7, the responses of regression predicated PSC, harvest efficiency, SWG, and economic profits to SR were compared for three different weather conditions [normal seasons with average spring rainfall (160 mm), dry seasons with 25% below normal rainfall (120 mm), and wet seasons with 25% above normal rainfall (200 mm)]. As expected, PSC decreased with increasing SR in all cases. Harvest efficiency, however, increased with increasing SR, indicating

Table 7–3. The linear relationships between GPFARM-Range model simulated steer weight gain from 1982 to 2012 between loam soil and clay loam or loam sandy soil across these stocking rates.†

Stocking rate	Clay loam soil		Loam sandy soil	
steer ha^{-1}				
0.20	$y = 0.99x$	$R^2 = 0.84$	$y = 0.98x$	$R^2 = 0.70$
0.33	$y = 0.98x$	$R^2 = 0.82$	$y = 0.96x$	$R^2 = 0.60$
0.44	$y = 0.98x$	$R^2 = 0.88$	$y = 0.95x$	$R^2 = 0.70$
0.66	$y = 0.98x$	$R^2 = 0.93$	$y = 0.94x$	$R^2 = 0.68$
0.88	$y = 0.97x$	$R^2 = 0.93$	$y = 0.95x$	$R^2 = 0.87$
1.10	$y = 0.95x$	$R^2 = 0.92$	$y = 0.91x$	$R^2 = 0.83$
1.32	$y = 0.94x$	$R^2 = 0.85$	$y = 0.89x$	$R^2 = 0.81$
0.2–0.88	$y = 0.97x$	$R^2 = 0.96$	$y = 0.95x$	$R^2 = 0.88$
1.10–1.32	$y = 0.94x$	$R^2 = 0.87$	$y = 0.90x$	$R^2 = 0.82$

† The slopes for these linear relationships were used as scaling factor to extend to these different soil types under different stocking rate levels.

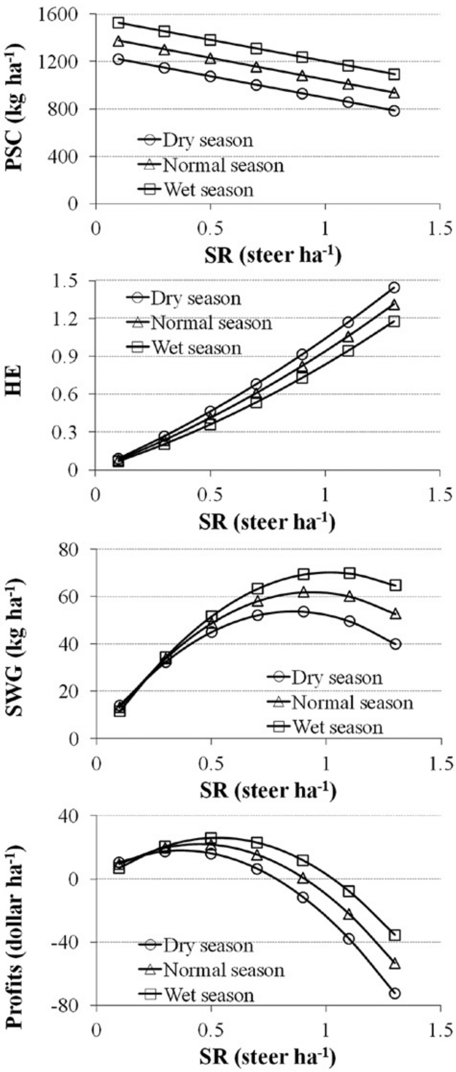

Fig. 7–7. Responses of peaking standing crop (PSC), harvest efficiency (HE), steer weight gain (SWG), and economic profits to stocking rate (SR, steer ha^{-1}) under dry (25% below average April–June rainfall, 120 mm), normal (160 mm), and wet (25% above average April–June rainfall, 200 mm) seasons. (The PSC, HE, and SWG were predicted from the equations in Table 7–2, where the soil water content was used as average value 0.18 cm^3 cm^{-3} from 1982 to 2012. The economic profits were estimated on the basis of the predicted SWG, cattle buy or sale price, and carry cost (Hart et al., 1988).

overgrazing at the high SR level (harvest efficiency > 1 indicates greater forage intake than forage production). The SWG increased quadratically with SR and showed higher values for wet seasons than for dry and normal seasons; the economic profits responded similarly to SR. In general, the biophysical optimum SR levels (that gave the highest SWG) generally increased from dry seasons to wet seasons. However, the SR values that yield the optimum economic returns were much lower than the biophysical optimums, which are associated with high harvest efficiency but also high risk of land degradation. Thus, the practical SR levels between 0.33 and 0.44 steer ha^{-1} are lower than the biophysical optimum SR and close to the experimental SR levels, avoiding negative economic profits and land degradation (overgrazing), but they can be higher for wet seasons than for dry seasons.

The soil water on 1 April showed positive influences on PSC and SWG and economic profits (Fig. 7–8). High soil water on 1 April produced higher PSC with lower harvest efficiency and produced higher SWG and economic profits than lower soil water on 1 April. The soil water effect on SWG and economic profits was pronounced with increased SR levels. The biophysical or economic optimum

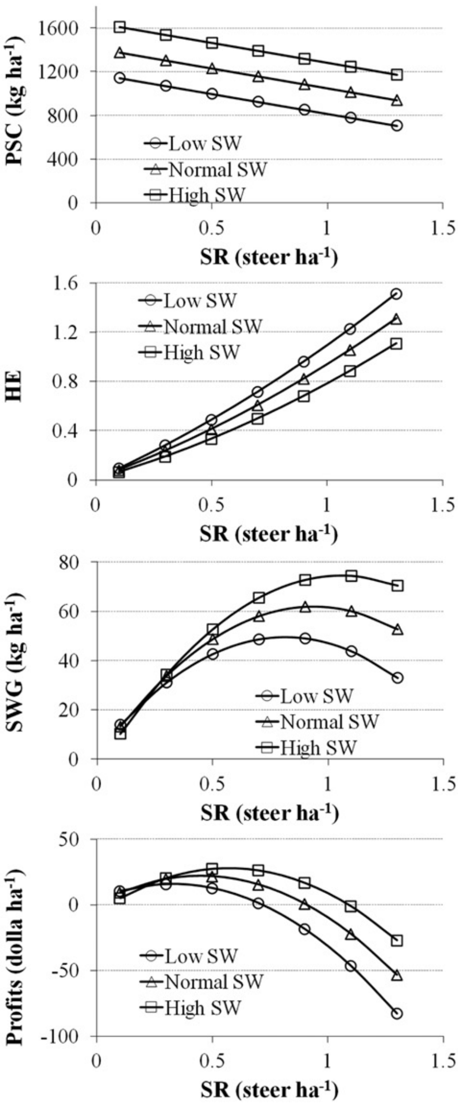

Fig. 7–8. Responses of regression predicted peaking standing crop (PSC), harvest efficiency (HE), steer weight gain per area (SWG), and economic profits to stocking rate (SR, steer ha^{-1}) as influenced by soil water conditions on 1 April (SW) (lower SW = 0.15 cm^3 cm^{-3}; normal SW = 0.18 cm^3 cm^{-3}, and high SW = 0.21 cm^3 cm^{-3}) under normal April to June rainfall conditions (160 mm). The economic profits were estimated on the basis of the predicted SWG, cattle buy or sale price, and carry cost (Hart et al., 1988).

SR levels increased from low to high soil water content on 1 April, suggesting that higher practical SR can be applied under higher soil water on 1 April than under lower soil water on 1 April.

Another influential factor to SR selections was the economic factor, such as cattle purchase or selling price. As shown in Fig. 7–9, the response of economic profits to SR as influenced by the cattle price showed that optimum SR levels were obtained at 0.3 to 0.5 steer ha^{-1} for a favorable price year and 0.1 to 0.3 steer ha^{-1} for the normal or unfavorable price year. A great difference in economic profits occurred with these different economic years (cattle price) and different weather conditions. Favorable prices for wet seasons produced high economic profits with relatively lower harvest efficiency (Fig. 7–7) when choosing a relatively high SR of 0.5 steer ha^{-1}. Unfavorable prices for dry seasons produced very low economic profits, and increasing SR can increase SWG (Fig. 7–7) but reduce the economic profits (Fig. 7–9).

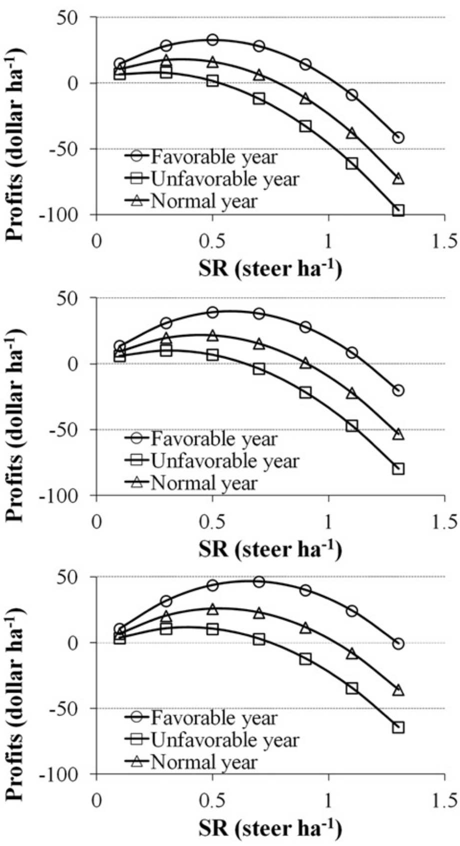

Fig. 7–9. Responses of regression predicted economic profits to stocking rate (SR, steer ha^{-1}) as influenced by cattle price (favorable price: buy at \$US1.76 and sell at \$US1.65; normal price: buy at \$US1.61 and sell at \$US1.48; unfavorable price: buy at \$US1.54 and sell at \$US1.32, according to Manley et al. [1997]) under normal April to June rainfall conditions (160 mm). The economic profits were estimated on the basis of the predicted SWG, cattle buy or sale price, and carry cost (Hart et al., 1988).

When extending these results to other soils, for example, clay loam and sandy loam soils, the responses of PSC, harvest efficiency, SWG, and economic profits to SR levels were similar, but with lower PSC (higher harvest efficiency), SWG, and economic profits compared with the results from loam soil, especially under high SR levels (Fig. 7–10). This result suggested that loam soil had an advantage in producing higher PSC and SWG with higher SR levels compared with clay loam and loam sandy soil. While under low SR levels, the response of harvest efficiency, SWG, and economic profits were very close among the three soil types.

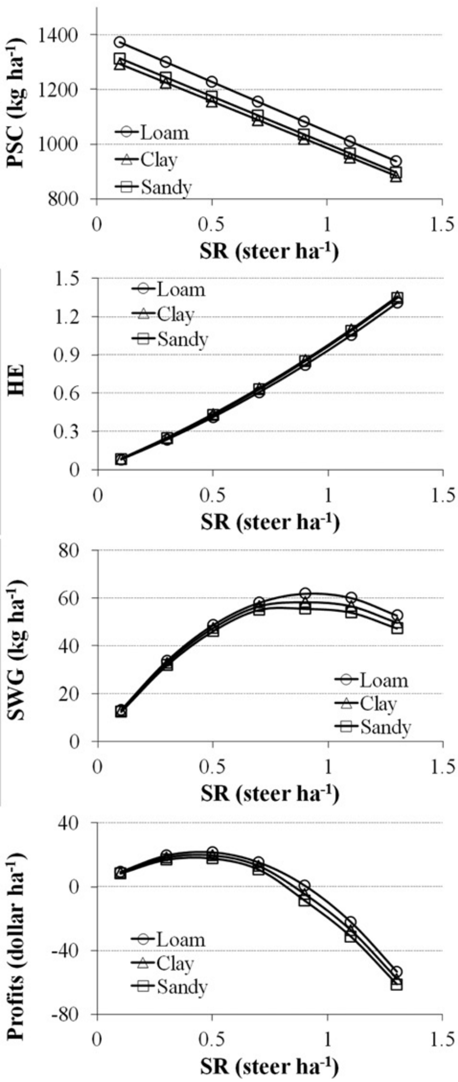

Fig. 7–10. Responses of regression predicted peaking standing crop (PSC), harvest efficiency (HE), steer weight gain per area (SWG), and economic profits to stocking rate (SR, steer ha^{-1}) as influenced soil types [the loam, clay loam, and loam sandy soils with extended regression equation predicted data from loam soil (Table 7–3)] under normal April to June rainfall conditions (160 mm). The economic profits were estimated on the basis of the predicted SWG, cattle buy or sale price, and carry cost (Hart et al., 1988).

Summary and Conclusions

On the basis of the GPFARM-Range model simulated long-term PSC data, simple regression equations can be developed in terms of rainfall from April to June, SR, and soil water content on 1 April to significantly improve the PSC predictions. Combining soil water content before the growing season and SR provides an accurate tool for ranchers to predict PSC before the grazing season and make reasonable stocking decisions in the region.

Including the predictions of PSC, SWG, and economic profits can be very helpful for ranchers in making better SR decisions, accounting for both economic return and environmental impact (land conservations). The regression equations can also be used to analyze the effects of weather and soil variations on the responses of PSC and SWG to SR levels. These regression equations are advantageous to previous methods, such as the Drought Calculator (Dunn et al., 2013), in that the regression equations consider both economic net return and environmental impacts and the coupled responses of PSC to SR and SWG to PSC and SR across various weather conditions. These equations can be used to develop a spreadsheet-based decisions support tool and help ranchers explore the tradeoffs between economic net return and environmental impacts (such as land degradation) as influenced by SR and weather variations and make better stocking decisions with reduced enterprise risks and land degradations on different soils across the northern mixed-grass prairie.

References

Andales, A.A., J.D. Derner, L.R. Ahuja, and R.H. Hart. 2006. Strategic and tactical prediction of forage production in northern mixed-grass prairie. Rangeland Ecol. Manag. 59:576–584. doi:10.2111/06-001R1.1

Andales, A.A., J.D. Derner, P.N.S. Bartling, L.R. Ahuja, G.H. Dunn, R.H. Hart, and J.D. Hanson. 2005. Evaluation of GPFARM for simulation of forage production and cow-calf weights. Rangeland Ecol. Manage. 58:247–255. doi:10.2111/1551-5028(2005)58[247:EOGFSO]2.0.CO;2

Bement, R.E. 1969. A stocking-rate guide for beef production on blue-grama range. J. Range Manage. 22:83–86. doi:10.2307/3896186

Biondini, M.E., B.D. Patton, and P.E. Nyren. 1998. Grazing intensity and ecosystem processes in a northern mixed-grass prairie. Ecol. Appl. 8:469–479. doi:10.1890/1051-0761(1998)008[0469:GIAEPI]2.0.CO;2

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. Am. J. Bot. 82:1024–1030. doi:10.2307/2446232

Currie, P.O., and G. Peterson. 1966. Using growing-season precipitation to predict crested wheatgrass yields. J. Range Manage. 19(5):284–288. doi:10.2307/3895721

Dahl, B.E. 1963. Soil moisture as predictive index of forage yield for the sandhills range type. J. Range Manage. 16:128–132. doi:10.2307/3895105

Derner, J.D., and R.H. Hart. 2007. Grazing-induced modifications to peak standing crop in northern mixed-grass prairie. Rangeland Ecol. Manage. 60:270–276. doi:10.2111/1551-5028(2007)60[270:GMTPSC]2.0.CO;2

Derner, J.D., R.H. Hart, M.A. Smith, and J.W. Waggoner. 2008a. Long-term cattle gain responses to stocking rate and grazing systems in northern mixed-grass prairie. Livest. Sci. 117:60–69. doi:10.1016/j.livsci.2007.11.011

Derner, J.D., B.W. Hess, R.A. Olson, and G.E. Schuman. 2008b. Functional group and species responses to precipitation in three semi-arid rangeland ecosystems. Arid Land Res. Manage. 22:81–92. doi:10.1080/15324980701784274

Dunn, G.H., M. Gutwein, L.J. Wiles, T.R. Green, A. Menger, and J. Printz. 2013. The Drought Calculator: Decision support tool for predicting forage growth during drought. Rangeland Ecol. Manage. 66(5):570–578. doi:10.2111/REM-D-12-00087.1

Eneboe, E.J., B.F. Sowell, R.K. Heitschmidt, M.G. Karl, and M.R. Haferkamp. 2002. Drought and grazing: IV. Blue grama and western wheatgrass. J. Range Manage. 55:73–79. doi:10.2307/4003266

Fang, Q.X., A.A. Andales, J.D. Derner, L.R. Ahuja, L. Ma, P.N.S. Bartling, J.L. Reeves, and Z. Qi. 2014. Modeling weather and stocking rate effects on forage and steer production in northern mixed-grass prairie. Agric. Syst. 129:103–114. doi:10.1016/j.agsy.2014.05.011

Freund, R.J., and R.C. Littell. 1991. SAS system for regression. 2nd ed. SAS Inst., Cary, NC.

Galt, D., F. Molinar, J. Navarro, J. Joseph, and J. Holechek. 2000. Grazing capacity and stocking rate. Rangelands 22(6):7–11.

Hanson, J.D., B.B. Baker, and R.M. Bourdon. 1992. SPUR2 Documentation and user guide. GPSR Tech. Rep. 1. USDA–ARS, Fort Collins, CO.

Hanson, J.D., J.W. Skiles, and W.J. Parton. 1988. A multispecies model for rangeland plant communities. Ecol. Modell. 44:89–123. doi:10.1016/0304-3800(88)90084-1

Hart, R.H., M.J. Samuel, P.S. Test, and M.A. Smith. 1988. Cattle, vegetation, and economic responses to grazing systems and grazing pressure. J. Range Manage. 41:282–286. doi:10.2307/3899379

Lauenroth, W.K., and O.E. Sala. 1992. Long-term forage production of north american shortgrass steppe. Ecol. Appl. 2:397–403. doi:10.2307/1941874

Manley, W.A., R.H. Hart, M.J. Samuel, M.A. Smith, J.W. Waggoner, and J.T. Manley. 1997. Vegetation, cattle, and economic responses to grazing strategies and pressures. J. Range Manage. 50:638–646. doi:10.2307/4003460

Milchunas, D.G., J.R. Forwood, and W.K. Lauenroth. 1994. Productivity of long-term grazing treatments in response to seasonal precipitation. J. Range Manage. 47:133–139. doi:10.2307/4002821

Patton, B.D., X. Dong, P.E. Nyren, and A. Nyren. 2007. Effects of grazing intensity, precipitation, and temperature on forage production. Rangeland Ecol. Manage. 60(6):656–665. doi:10.2111/07-008R2.1

Poppi, D.P. 1996. Predictions of food intake in ruminants from analyses of food composition. Aust. J. Agric. Res. 47:489–504. doi:10.1071/AR9960489

Redmon, L.A., F.T. McCollum, III, G.W. Horn, M.D. Cravey, S.A. Gunter, P.A. Beck, J.M. Mieres, and R.S. Julian. 1995. Forage intake by beef steers grazing winter wheat with varied herbage allowances. J. Range Manage. 48:198–201. doi:10.2307/4002420

Reeves, J., J. Derner, M. Sanderson, J. Hendrickson, S. Kronberg, M. Petersen, and L. Vermeire. 2014. Seasonal weather influences on yearling beef steer production in C_3-dominated Northern Great Plains rangeland. Agric. Ecosyst. Environ. 183:110–117. doi:10.1016/j.agee.2013.10.030

Reeves, J.L., J.D. Derner, M.A. Sanderson, M.K. Petersen, L.T. Vermeire, J.R. Hendrickson, and S.L. Kronberg. 2013a. Seasonal temperature and precipitation effects on cow–calf production in northern mixed-grass prairie. Livest. Sci. 155:355–363. doi:10.1016/j.livsci.2013.04.015

Reeves, J., J. Derner, M. Sanderson, M. Petersen, L. Vermeire, J. Hendrickson, and S. Kronberg. 2013b. Temperature and precipitation affect steer weight gains differentially by stocking rate in northern mixed-grass prairie. Rangeland Ecol. Manage. 66(4):438–444. doi:10.2111/REM-D-12-00157.1

Sala, O.E., W.J. Parton, L.A. Joyce, and W.K. Lauenroth. 1988. Primary production of the central grassland region of the United States. Ecology 69:40–45. doi:10.2307/1943158

Smart, A.J., J.D. Derner, J.R. Hendrickson, R.L. Gillen, B.H. Dunn, E.M. Mousel, and K.C. Olson. 2010. Effects of grazing pressure on efficiency of grazing on North American Great Plains rangelands. Rangeland Ecol. Manage. 63(4):397–406. doi:10.2111/REM-D-09-00046.1

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 Ecol. Manage. 60:146–153. doi:10.2111/05-099R4.1

Stevenson, A., R.E. Baumgartner, and G.E. Schuman. 1984. High Plains Grasslands Research Station detailed soil survey. USDA Publ. 1–84/1C/3.62. Wyoming Agricultural Experiment Station, Laramie, WY.

Torell, L.A., K.C. McDaniel, and V. Koren. 2011. Estimating grass yield on blue grama range from seasonal rainfall and soil moisture measurements. Rangeland Ecol. Manage. 64:56–66. doi:10.2111/REM-D-09-00107.1

USDA–NASS. 2014. Economics and prices. USDA–NASS. http://www.nass.usda.gov/Statistics_by_Subject/Economics_and_Prices/index.asp (accessed 27 June 2014).

Wiles, L.J., G. Dunn, J. Printz, B. Patton, and A. Nyren. 2011. Spring precipitation as a predictor for peak standing crop of mixed-grass prairie. Rangeland Ecol. Manage. 64(2):215–222. doi:10.2111/REM-D-09-00024.1