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Nondestructive Estimation of Standing Crop and Fuel Moisture Content in Tallgrass Prairie☆

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ABSTRACT

Accurate estimation of standing crop and herbaceous fuel moisture content (FMC) are important for grazing management and wildfire preparedness. Destructive sampling techniques have been used to accurately estimate standing crop and FMC, but those techniques are laborious and time consuming. Existing nondestructive methods for estimating standing crop in tallgrass prairie have limitations, and few studies have examined nondestructive estimation techniques for FMC in this environment. Therefore, our objective was to develop robust models for nondestructive estimation of standing crop and FMC in tallgrass prairie. We calibrated and validated stepwise multiple linear regression (SMLR) and artificial neural network (ANN) models for standing crop and FMC using data collected in tallgrass prairies near Stillwater, Oklahoma. Day of year (DOY), canopy height (CH), Normalized Difference Vegetation Index (NDVI), and percent reflectance in five wavelength bands were candidate input variables for the models. The study spanned two growing seasons and nine patches located within three pastures under patch burn management, and the resulting data set with >3 000 observations was split randomly with 85% for model calibration and 15% withheld for validation. Standing crop ranged from 0 to 852 g m^{-2}, and FMC ranged from 0% to 204%. With DOY, CH, and NDVI as predictors, the SMLR model for standing crop produced a root mean squared error (RMSE) of 119 g m^{-2} on the validation data, while the RMSE of the corresponding ANN model was 116 g m^{-2}. With the same predictors, the SMLR model for FMC produced an RMSE of 26.7% compared with 23.8% for the corresponding ANN model. Thus, the ANN models provided better prediction accuracy but at the cost of added computational complexity. Given the large variability in the underlying datasets, the models developed here may prove useful for nondestructive estimation of standing crop and FMC in other similar grassland environments.

Introduction

Grasslands and grazing systems are essential to agricultural communities in the US Southern Great Plains (SGP) and in similar climatic regions worldwide. More than 55 million ha are classified as grassland or pasture in the SGP states of Kansas, Oklahoma, and Texas (NASS, 2012). Accurate estimates of dynamic grassland vegetation parameters are needed for research, grazing management decisions (Benkobi et al., 2000), and wildfire preparedness (Chuvieco et al., 2002). Two key parameters in the context of grazing management and wildfire preparedness are standing crop and herbaceous fuel moisture content (FMC). Destructive measurement techniques, such as hand clipping, have often been used to estimate standing crop and FMC at the quadrat scale. Hand clipping is considered to be objective and accurate, but it is also laborious and time consuming, particularly when sampling large, heterogeneous areas. Ocular estimates of standing crop have been used to avoid destructive sampling in rangelands (Twidwell et al., 2009), but these ocular estimates are subjective and have limited precision.

In contrast, spectral reflectance data can potentially provide nondestructive, objective, and relatively inexpensive estimates of standing crop and FMC. An attractive feature of reflectance-based methods is their potential, when combined with satellite observations, to monitor changes on a global scale. For example, Normalized Difference Vegetation Index (NDVI) has been widely used in assessments of grassland biomass (Paruelo et al., 1997; Tarr et al., 2005; Zhang et al., 2016). However, when used alone, NDVI showed a weak relationship with standing forage biomass ($r^2 = 0.13$) in tallgrass prairie in Kansas (Olson and

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Cochran, 1998). In that study, prediction of biomass was improved by also using day of year (DOY) and canopy height (CH). Similarly, in another study conducted in rangeland in northern California, the plant height-ground cover interaction was strongly correlated with forage biomass with correlation coefficients ranging from 0.538 to 0.988 (Evans and Jones, 1958).

Just as with standing crop, the use of nondestructive reflectance-based methods may also overcome some of the obstacles related with field sampling of FMC. For example, FMC of grasslands and shrub lands was accurately estimated ($r^2 = 0.907$ and 0.732) using a 5-yr time series (2001 − 2005) of Terra Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI in Cabañeros National Park in Central Spain (Yebra et al., 2008). Similarly, multitemporal composites derived from 4 yr of NDVI data from the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) along with surface temperature and day of year were used to estimate FMC (R^2 over 0.8) in Mediterranean grassland in central Spain (Chuvieco et al., 2004).

Two key methods used to estimate vegetation parameters from reflectance data are stepwise multiple linear regression (SMLR) and Artificial Neural Networks (ANN) (Olson and Cochran, 1998). SMLR is an automated process of building a model by sequentially adding or removing variables based on a specified statistical criterion. An ANN is a model consisting of multiple interconnected processing elements, called *nodes* or *neurons,* that respond dynamically to external inputs (Warner and Misra, 1996). One main advantage of ANNs over SMLR models is that ANNs do not require linear relationships between the input and output variables (Sudheer et al., 2010). In preliminary work, we discovered that the models of Olson and Cochran (1998), although developed in a tallgrass prairie environment similar to our study area and in relatively close geographic proximity, performed poorly for standing crop estimation at our sites ($R^2 < 0$). And, we are not aware of any prior studies that developed nondestructive methods to estimate FMC specifically for tallgrass prairie ecosystems. Thus, there was a need to develop improved methods for nondestructive estimation of these key dynamic vegetation parameters in tallgrass prairie.

In this study, our objective was to develop robust models for nondestructive estimation of standing crop and FMC in tallgrass prairie. We calibrated and validated both stepwise multiple linear regression (SMLR) and artificial neural network (ANN) models for standing crop and FMC using data collected in grazed tallgrass prairies under patch burn management on a 3-yr rotation near Stillwater, Oklahoma. Measurements were conducted from May to December of 2012 and from March to November of 2013, and during this time, the sites experienced diverse weather conditions, from drought in the 2012 growing season to normal precipitation during the 2013 growing season.

Materials and Methods

Study Area

Research was conducted in tallgrass prairie at the Oklahoma State University Range Research Station located near Stillwater, Oklahoma. Major vegetation species were little bluestem (*Schizachyrium scoparium* [Michx]), big bluestem *(Andropogon gerardii),* Indiangrass *(Sorghastrum nutans),* post oak *(Quercus stellata),* and eastern redcedar *(Juniperus virginiana).* The dominant soils at this site included the Grainola series (fine, mixed, thermic Vertic Haplustalf) covering approximately 60% of the area and the Coyle series (fine-loamy, siliceous, thermic Udic Argiustoll) covering approximately 35% of the area (Gillen et al., 1990).

The study site consisted of three pastures ranging in size from 50 to 63 ha. Those pastures were subdivided into six approximately equal-sized unfenced patches. These patches were used in a patch burning treatment designed to increase ecological heterogeneity while preventing woody plant encroachment (Fuhlendorf and Engle, 2004). Each year, two of the six patches within each pasture were burned: one during the latter months of the dormant season (March − April) and one during the latter months of the growing season (July − October). The patch burning sequence has been continuous since the pastures were established in 1999. The experimental design was a randomized complete block with three treatments (i.e., patches with three different levels of time since burning) and three replications (i.e., the three pastures) (Fuhlendorf and Engle, 2004). Each pasture was moderately grazed by beef cows from 1 December to 1 September at a stocking rate of 0.15 animal units ha^{-1}. Animals grazed freely across the burned and unburned patches. In the present study, sampling occurred only in the nine patches in the growing season burn treatment. Although some samples were collected in November and December, after one-third of the patches had been burned, those samples were not treated differently from the others in our analysis. We did not consider time since fire as a factor in our models because we wanted the models to use only relatively easily obtainable data and for many "real world" locations, time since fire is unknown.

Measurement Procedures

Standing crop and FMC were measured at 12 locations in each of the 9 study patches once every 2 wk during the 2012 and 2013 growing seasons. This resulted in > 3 000 individual samples. Measurements involved hand-clipping all herbaceous vegetation in a 0.25-m^2 quadrat, weighing the fresh sample, and drying the vegetation for 3 d at 70° C. Standing crop was calculated on an oven dry weight basis, and FMC was calculated as the ratio of the weight of water in the sample to its dry weight. Canopy height for standing crop was also measured at three points in the quadrat, and the mean value was recorded at the time of sampling.

Canopy reflectance data were collected at each sampling location before clipping using a hand-held multispectral radiometer (MSR5R, Cropscan, Inc., Rochester, MN) at 2 m above ground between 1200 and 1700 hours. The radiometer's field of view at height of 2 m is approximately 0.79 m^2, which is three times larger than our quadrat size of 0.25 m^2. The smaller quadrat size was chosen to match that of Olson and Cochran (1998) and other similar studies. Larger quadrats significantly increase the time and effort required for clipping. However, the scale mismatch between the radiometer field of view and the clipped quadrat is a limitation of our study, which may artificially inflate the error statistics for our nondestructive estimation methods. The radiometer measured percentage reflectance in five bands in the 460 − 1750 nm region (approximate center wavelengths = 485, 560, 660, 830, and 1 650 nm). Radiometer calibration was conducted before the start of each growing season using diffusing opal glass, alternately held over the up-and-down sensors facing the same incident irradiation to calibrate the up-and-down sensors relative to each other (Xue et al., 2004). Normalized Difference Vegetation Index (NDVI) was calculated on the basis of the reflectance at wavelengths of 660 and 830 nm (Rouse et al., 1974). We also explored using the soil-adjusted vegetation index (Huete, 1988) as an alternative to NDVI, but no statistically significant advantages were observed.

Modeling Procedures

As a preliminary analysis, we performed a simple linear regression of NDVI versus standing crop. The purpose of this analysis was to facilitate comparison of our data with the earlier data of Olson and Cochran (1998) and to illustrate the inadequacy of NDVI alone as a predictor of standing crop. Subsequently, progressive combinations of day of year (DOY), canopy height (CH), NDVI, and percent reflectance in five bands were used to estimate standing crop and FMC via SMLR models (Table 1). SMLR fits an observed dependent data set using two or more explanatory variables in a linear equation. SMLR attempts to identify the major variables that influence the dependent variable using a stepwise process of adding and removing terms from a multilinear model.

Table 1
Root Mean Square Error (RMSE) values for stepwise multiple linear regression (SMLR) and artificial neural network (ANN) models for standing crop and herbaceous fuel moisture content (FMC). The RMSE values are for the validation data which were not used in model calibration. The input variables include day of year (DOY), canopy height (CH), normalized difference vegetative index (NDVI), and percent reflectance measured in five bands.

Model	Input variables	SMLR		ANN	
		Standing crop	FMC	Standing crop	FMC
		g m^{-2}	%	g m^{-2}	%
1	DOY	181	43.8	155	27.9
2	DOY + CH	126	39.9	123	31.1
3	DOY + NDVI	134	27.4	129	24.5
4	DOY + CH + NDVI	119	26.7	116	23.8
5	DOY + CH + five bands	122	25.9	118	23.6

We used the *stepwiselm* function in Matlab version R2016a (Mathworks Inc., 2016). Importance for the candidate independent variables was determined by the P value for the F-statistic on the change in the model's sum of squared errors by adding or removing the variables. SMLR starts with only a constant term in the model and then uses forward and backward stepwise regression to construct the final model. The routine adds a variable to the model in a given step if the P value for that variable is < 0.05 and is the lowest of all the P values for the variables not currently in the model. The fitting process is repeated until no excluded variables have $P < 0.05$. Then the routines remove a variable from the model in a given step if its P value is > 0.10 and is the largest of all the P values for the variables in the model. The fitting process is continued until no included variables have $P > 0.10$; however, variables with P values below this threshold are retained if they are contained in a significant interaction term.

The general equation is as follows:

$$Y = P_0 + P_1X_1 + \ldots + P_NX_N \tag{1}$$

where P_i ($i = 0, 1, \ldots, N$) are the parameters and X_i ($i = 1, \ldots, n$) are the explanatory variables. We used 85% of the data (randomly selected) for calibration and the remaining 15% for validation. We used the coefficient of determination (R^2), root mean square error (RMSE), and bias to evaluate the predictive quality of the models. Lilliefors test was also used to test the model residuals for normality using the *lillietest* function in Matlab.

In addition to SMLR, we evaluated the ability of ANNs to estimate standing crop and FMC. An ANN is a mathematical structure for representing potentially nonlinear processes by formulating the relationship between inputs and outputs. A three-layer feed-forward network architecture was used with the input layer consisting of up to eight input variables (DOY, CH, NDVI, and percent reflectance in five bands). The ANN models included 1 hidden layer consisting of 15 neurons and 1 output layer. A feed-forward network is an architecture where each variable in the input layer is connected to each neuron in the hidden layer for processing. The processing was accomplished by passing the input signal for each neuron through a hyperbolic tangent transfer function. Each neuron in the hidden layer is also connected to the single neuron in the output layer, which represents the dependent variable, in this case standing crop or FMC. A linear transfer function was applied in the output layer. Each connection has a certain weight, a numerical estimation of the connection strength, which is optimized during training.

We used the *nntraintool* function in Matlab with the Bayesian regularization-training algorithm to train the model. For the ANN, 70% of the data were used for training (calibration) while 15% of the data were used for the testing phase, which is part of the training process. The data in the testing phase are intended to prevent overfitting of the ANN. The remaining 15% of the data were used to validate the ANN models (Demuth and Beale, 1992). We used the coefficient of determination (R^2), root mean square error (RMSE), and bias to evaluate the predictive quality of the ANN models. The relative importance of the candidate independent variables was determined on the basis of the connection weights in the trained ANN model using the 'weight method' as described in Gevrey et al. (2003). For both SMLR and ANN models, we also calculated the RMSE-observations standard deviation ratio (RSR) to allow us to categorize the quality of model performance using the scheme of Moriasi et al. (2007).

To quantify the effects of measurement uncertainty associated with the clipping method and our nondestructive methods of estimating standing crop and FMC, we estimated the sample sizes that would be needed to estimate the mean of each parameter by each method to within a desired degree of precision. The sample size affects the standard error, which in turn affects the width of confidence intervals (Gardner and Altman, 1986). For the clipping method, we estimate the required sample number (n) to estimate standing crop or FMC to within 10% of their respective mean values with 95% confidence using

$$n = \frac{\left(z_{\alpha/2}\right)^2 \sigma^2}{E^2} \tag{2}$$

where $z_{\alpha/2} = 1.96$, the z-score corresponding to an $\alpha = 0.05$, σ is the population standard deviation of the parameter of interest for a given patch on a particular date, and E is the acceptable level of error or uncertainty in the estimate of the mean (Ott and Longnecker, 2001). For the clipping method, we approximated the unknown σ as the mean value across all sampling dates and patches of the within-patch sample standard deviation for the parameter of interest. The value of E was set equal to 0.10 times the mean value across all sampling dates and patches of the parameter of interest. Exact methods for determining confidence intervals on neural network predictions are complex and not yet well developed, thus we also used Eq. (2) to approximate the required sample size for neural network-based predictions of standing crop and FMC. This required the slight modification that the necessary sample standard deviation and sample mean were computed as the corresponding mean values across all sampling dates and patches of the within-patch statistics (sample standard deviation or mean) for the model estimates of the parameter of interest (standing crop or FMC). To ensure unbiased intercomparisons, the required sample sizes for the multiple regression models were calculated in the same way as those for the neural network models.

Results and Discussion

Standing crop and FMC exhibited large variability in space and time, with standing crop values ranging from 0 to 852 g m^{-2} and FMC ranging from 0% to 204%. The standing crop was positively related to NDVI; however, the relationship was relatively weak with an $r^2 = 0.32$ ($P < 0.05$) and RMSE of 152 g m^{-2} (Fig. 1). Similarly, standing crop was positively but weakly related to NDVI in tallgrass prairie in Kansas (Olson and Cochran, 1998). These results reinforce the fact that NDVI alone cannot be used to accurately estimate standing crop in tallgrass prairie. We also tested the multiple regression model described by Olson and Cochran (1998) using NDVI, CH, and DOY for estimating standing crop in our dataset. This model proved not to be applicable in our study area ($R^2 = -3.76$ and RMSE of 401 g m^{-2}). This demonstrates the need to develop new and robust models for estimating standing crop and FMC in tallgrass prairie.

Stepwise Multiple Linear Regression (SMLR) Models

Estimation of Standing Crop

Five different regression models for estimating standing crop were evaluated (see Table 1). Compared with the model with DOY as the only predictor, adding CH substantially improved the prediction

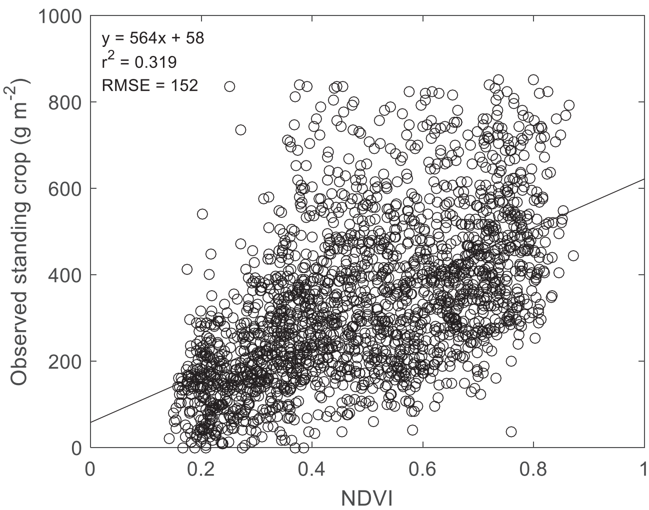

Fig. 1. Linear regression of standing crop versus Normalized Difference Vegetation Index (NDVI).

accuracy for standing crop, reducing the RMSE for the validation set from 181 g m^{-2} to 126 g m^{-2} (see Table 1). Adding NDVI instead of CH also improved the model, but to a lesser degree (RMSE = 134 g m^{-2}). Prediction accuracy was further improved by including both CH and NDVI, resulting in RMSE = 119 g m^{-2}. Replacing NDVI with the reflectance data from all five bands resulted in a slight decrease in the prediction accuracy for standing crop. Since NDVI data can be measured with simpler handheld sensors, there appears to be no advantage to obtaining and using reflectance data in all five bands measured by the radiometer employed in this study, if one's goal is to estimate standing crop in tallgrass prairie. Therefore, we selected the SMLR model with DOY, CH, and NDVI for further analyses (see model 4, Table 1). The terms and coefficients for that model are given in Table 2.

The SMLR model 4 estimated standing crop for the validation data with $R^2 = 0.598$ and RMSE = 119 g m^{-2} (Fig. 2). The SMLR model performance in estimating standing crop was classified as satisfactory on the basis of the RSR value of 0.63. The best SMLR model of Olson and Cochran (1998) had a similar model structure, using NDVI, CH, and DOY as predictors, but it lacked the interaction terms. It achieved a greater $R^2 = 0.83$ and lower RMSE = 73 g m^{-2} on the data set for which it was calibrated. However, that data set spanned only one growing season, included about two orders of magnitude fewer observations than our data set, and did not include validation data.

On the basis of our dataset, with the clipping method at least 42 0.25-m^2 samples would be needed to estimate the mean standing crop for a particular patch to within ±10% with 95% confidence (Table 3). When using the SMLR model, only 15 radiometer measurement locations would be required to obtain the same precision. The estimated sample number required for the clipping method in our study is consistent with the results of Brummer et al. (1994). They reported that 52 0.18-m^2 samples or 26 − 36 0.36-m^2 samples would be needed to estimate standing crop of mid and tall grasses in the Sandhills of Nebraska with the same level of precision we specified.

Table 2
Parameter estimates for each term in stepwise multiple regression model #4 for standing crop and FMC along with standard errors (SE), and *p*-values.

	Standing crop (g m^{-2})			FMC (%)		
Ind. Variables	Estimate	SE	*p*-values	Estimate	SE	*p*-values
Intercept	156	20.9	< 0.001	-23.9	4.99	< 0.001
DOY	-0.598	0.106	< 0.001	0.065	0.025	0.009
CH (m)	828	75.0	< 0.001	-204	17.8	< 0.001
NDVI	-391	66.0	< 0.001	348	15.6	< 0.001
DOY × CH	-1.32	0.324	< 0.001	0.657	0.076	< 0.001
DOY × NDVI	3.39	0.351	< 0.001	-0.739	0.082	< 0.001

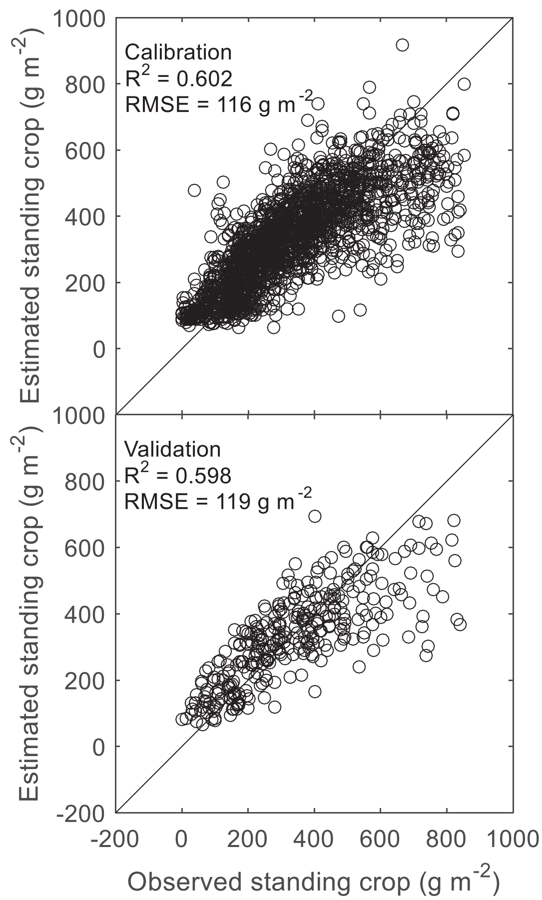

Fig. 2. Estimation of standing crop using stepwise multiple linear regression model #4. Independent variables included day of year, canopy height and NDVI. The model was calibrated using 85% of the data and validated using the remaining 15%.

The SMLR model underestimated standing crop for levels above about 600 g m^{-2}. A Lilliefors test on the residuals indicated that the residuals were not normally distributed ($P < 0.05$). This may be due to the inability of SMLR to describe nonlinear relationships between the predictors and standing crop. Estimation of standing crop for grasslands with values > 500 g m^{-2} may necessitate the use of nonlinear functions (Pearson et al., 1976). The problem may arise from the radiometer's inability to equally detect and integrate reflectance from the lower layers of the canopy. Moreover, the mismatch in the scale of radiometer and clipping method could have reduced the performance of the models in estimating standing crop. We explored the use of quadratic terms in the SMLR models, but they also failed to produce normally distributed residuals. Nonlinear relationships between NDVI and a green biomass index have been developed, but these have not yet been adapted for use in multivariate models like the ones in this study (Santin-Janin et al., 2009).

Estimation of Herbaceous Moisture Content (FMC)

Compared with the model with DOY as the only predictor, adding CH marginally improved the prediction accuracy for FMC, reducing the RMSE for the validation set from 43.8% to 39.9% (see Table 1). Adding

Table 3
Number of samples required to estimate mean standing crop or FMC for a particular patch on a particular day with a 95% confidence interval equal to ±10% of the mean for three different approaches: 1) clipping; 2) SMLR model #4; or 3) ANN model #4.

	Clipping	SMLR	ANN
Standing Crop	42	15	18
FMC	20	12	8

NDVI as a predictor resulted in a greater reduction of the error than adding CH, bringing the RMSE down to 27.4%. Prediction accuracy was slightly improved by including both CH and NDVI, resulting in an RMSE value of 26.7% for the validation set. Replacing NDVI with the reflectance data from all five bands resulted in an additional small improvement to the prediction accuracy for FMC. For consistency with the standing crop model, we selected for further analyses the SMLR model for FMC with DOY, CH, and NDVI as predictors (see model 4, Table 1). The terms and coefficients for that model are also given in Table 2.

The SMLR model estimated FMC for the validation data set with $R^2 = 0.632$ and RMSE = 26.7% (Fig. 3). The SMLR model performance in estimating FMC was classified as satisfactory on the basis of the RSR value of 0.60. The SMLR model of Chuvieco et al. (2002) estimated FMC of grasslands in Spain with a higher R^2 (0.84) but an average error of 27.1%, similar to the RMSE in our study. Their greater R^2 value may be associated with their small data set and low frequency of data collection. They used only three reflectance measurements per year from 1996 to 1999 with only one measurement in 1999, while in our study, measurements were collected in biweekly intervals. As a result, our data set included thousands of observations while theirs included < 30. In their follow-up study, FMC was again estimated with higher R^2 values (> 0.88) than in our study but with standard errors > 30%, larger than the RMSE in our study (Chuvieco et al., 2004). The structure of their model was similar to ours in that DOY and NDVI were the primary predictors of FMC, suggesting that it may be possible to design a globally applicable empirical model for grassland FMC based on these two inputs.

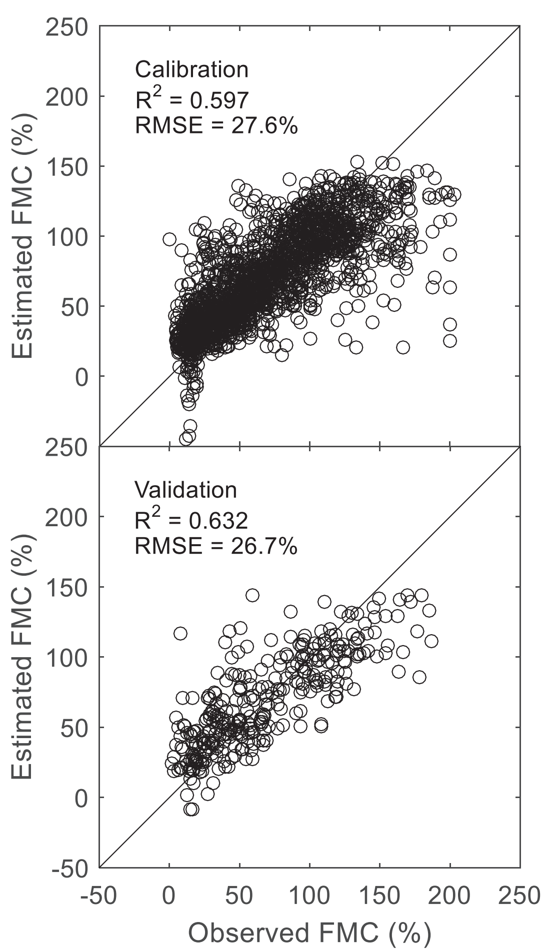

Fig. 3. Estimation of Fuel Moisture Content (FMC) using stepwise multiple linear regression model #4. Independent variables included day of year, canopy height and NDVI. The model was calibrated using 85% of the data and validated using the remaining 15%.

On the basis of our dataset, with the clipping method at least 20 samples would be necessary to estimate the mean FMC for a particular patch to within ± 10% of the mean with 95% confidence (Table 3). When using the SMLR model, only 12 radiometer measurement locations would be required to obtain the same precision. SMLR model 4 underestimated FMC for levels above about 150%. A Lilliefors test on the residuals indicated that the residuals were not normally distributed ($P < 0.05$). This may be due to the inability of SMLR to describe nonlinear relationships between predictors and FMC as we have noted for AGB. Prior research relating spectral reflectance to FMC has also shown that correlation with FMC was strongest at low FMC values < 100% and weaker at high FMC values (Danson and Bowyer, 2004). The authors in that study hypothesized that changes in specific leaf weight and leaf internal structure may be influencing the relationship between FMC and spectral reflectance (Danson and Bowyer, 2004).

Artificial Neural Network (ANN) Model

Estimation of Standing Crop

Since an ANN model was better in estimating standing crop than an SMLR model in tallgrass prairie in Kansas (Olson and Cochran, 1998), we also evaluated ANN performance in our data set. We tested the same five combinations of input variables for the ANN as for the SMLR models described earlier. Compared with the model with DOY as the only predictor, adding CH substantially improved the prediction accuracy for standing crop, reducing the RMSE for the validation set from 155 g m^{-2} to 123 g m^{-2} (see Table 1). Adding NDVI instead of CH also improved the model, but to a lesser degree (RMSE = 129 g m^{-2}), consistent with the pattern observed in the SMLR models. Prediction accuracy was further improved by including both CH and NDVI, resulting in an RMSE value of 116 g m^{-2} for the validation set. Replacing NDVI with the reflectance data from all five bands again resulted in a slight decrease in prediction accuracy for standing crop on the validation data set. As in the prior sections, we selected for further analyses the ANN model for standing crop with DOY, CH, and NDVI as predictors (see model 4, Table 1).

On the basis of the weight method, DOY was the most important predictor variable in the ANN model for standing crop, with a relative importance of 45.7% (Table 4). Both CH and NDVI showed lower and roughly equal importance. The disadvantage of including CH in models for standing crop or FMC is that CH typically must be measured by a person in the field rather than remotely sensed. Some remote or automated sensing techniques such as light detection and ranging (LIDAR) and automated terrestrial laser scanning (ATLS) show strong potential for unattended canopy height measurement (Bork and Su, 2007; Eitel et al., 2016). These technologies are creating new possibilities for nondestructive estimation of dynamic vegetation parameters.

The trained ANN model 4 estimated standing crop for the validation data with $R^2 = 0.622$ and RMSE = 116 g m^{-2} (Fig. 4). The ANN model performance in estimating standing crop was classified as satisfactory on the basis of the RSR value of 0.61. This ANN model performed slightly better than SMLR model 4 in estimating standing crop ($R^2 = 0.62$ vs. 0.60, RMSE = 116 g m^{-2} vs. 119 g m^{-2}). The ANN model for standing crop actually showed a greater performance advantage relative to the SMLR model for the calibration dataset ($R^2 = 0.66$ vs. 0.60 and RMSE

Table 4
Relative importance (RI) for each input variable in the trained ANN model #4 for standing crop and FMC. The relative importance is shown as percentage.

	DOY	CH	NDVI
		%	
Standing crop	45.7	26.3	28.0
FMC	48.2	21.5	30.2

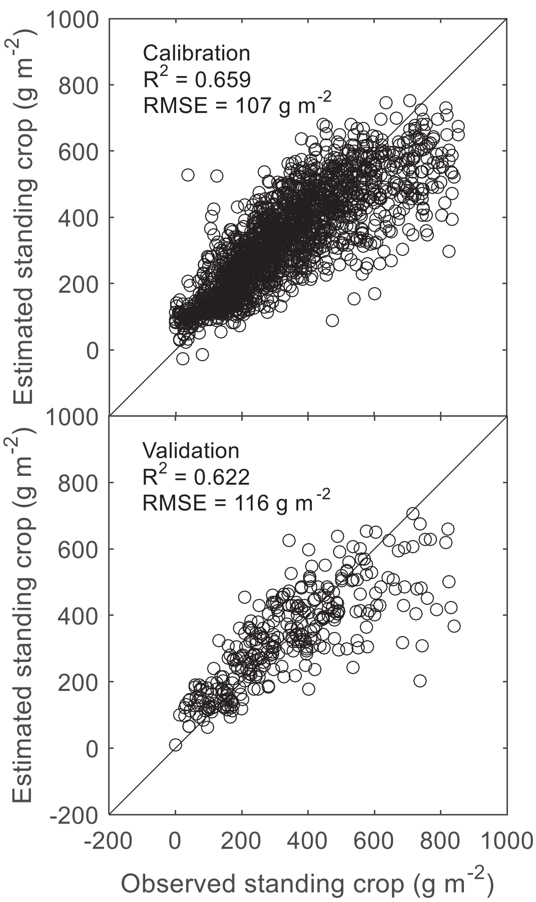

Fig. 4. Estimation of standing crop using artificial neural network model # 4. Independent variables included day of year, canopy height and NDVI. The model was calibrated using 85% of the data and validated using the remaining 15%.

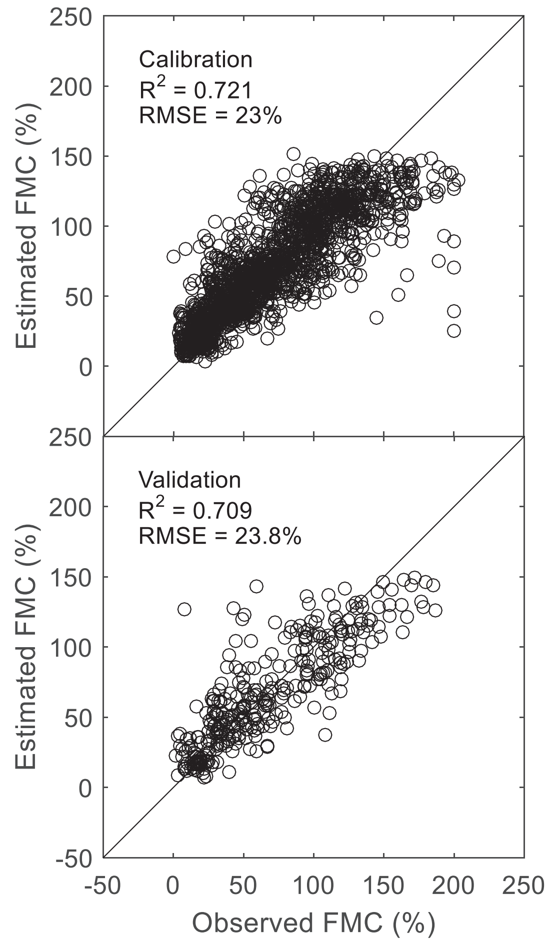

Fig. 5. Estimation of Fuel Moisture Content (FMC) using artificial neural network model # 4. Independent variables included day of year, canopy height and NDVI. The model was calibrated using 85% of the data and validated using the remaining 15%.

$= 107$ g m^{-2} vs. 116 g m^{-2}), but that advantage decreased on the validation dataset. Although an ANN model for standing crop in tallgrass prairie outperformed an SMLR model in a prior study, neither of those models was tested with an independent validation set (Olson and Cochran, 1998). The superior fitting capabilities of ANN models over SMLR models during the calibration phase do not necessarily result in more accurate predictions when both types of models are confronted with new data. A minimum of 18 sampling locations would be needed to estimate mean standing crop for a particular pasture or patch on a particular day with a 95% confidence interval equal to $\pm 10\%$ of the mean using ANN model 4 (see Table 3). This is similar to the 15 samples that would be needed with the SMLR model and far fewer than the 42 samples that would be needed for the clipping method.

Like the SMLR model, the ANN model also typically underestimated standing crop for levels above 600 g m^{-2}. A Lilliefors test on the residuals indicated that the residuals were not normally distributed ($P < 0.05$). This could be due to an inadequate number of observations with high standing crop levels in the calibration data set for the ANN model. This suggests that there is still further room for improvement in the input data, the ANN structure, or the ANN training process. Although the ANN model should be able to account for nonlinearity in the relationships between the predictors and response variable, the ANN model showed similar deficiencies at high levels of standing crop as the SMLR model in our study.

Estimation of Herbaceous Moisture Content (FMC)

Using the same set of input variables, the trained ANN model 4 estimated FMC for the validation set with $R^2 = 0.709$ and RMSE $= 23.8\%$ (Fig. 5). The ANN model performance in estimating FMC was classified as good based on the RSR value of 0.54. DOY was again the most important input variable while CH was the least important variable in this ANN model for FMC (see Table 4). The ANN model showed better prediction accuracy than the SMLR model in estimating FMC ($R^2 = 0.71$ vs. 0.63, RMSE $= 23.8\%$ vs. 26.7%) (see Fig. 5 vs. Fig. 3). The RMSE for the ANN model estimates of FMC was equal to the average error of the best SMLR model among those developed by Chuvieco et al. (2002). Few, if any, prior studies have directly compared ANN and SMLR models for estimating FMC, and the superior performance of the ANN model in our study suggests ANN models may have good potential for improving FMC estimation in other contexts (e.g., remote sensing of FMC).

Despite the overall good performance of the ANN model for estimating FMC, there was still an underestimation of FMC for values over about 150%. This underestimation again might be due to fewer observations with high FMC values in training the ANN model. A Lilliefors test on the residuals indicated that the residuals were not normally distributed ($P < 0.05$). A minimum of 8 sampling locations would be needed to estimate mean FMC for a particular patch on a particular day with a 95% confidence interval equal to $\pm 10\%$ of the mean using ANN model 4 (see Table 3). This is fewer than the 12 samples that would be needed with the SMLR model and far fewer than the 20 samples that would be needed for the clipping method.

Management Implications

Both multiple regression and artificial neural network approaches led to robust models for nondestructive estimation of standing crop and FMC in tallgrass prairie. These models are based on in situ measurements of canopy height and NDVI and require fewer sampling locations and less manual labor than traditional clipping approaches for determining standing crop and FMC. These nondestructive approaches are expected to prove useful for future studies of grassland vegetation dynamics, for grazing systems research and management, and for fire danger research and monitoring. The models were calibrated and validated using a data set with > 3 000 samples and were able to estimate standing crop and FMC for tallgrass prairie in Oklahoma with accuracy comparable with that reported for prior models developed with far smaller data sets.

The neural network approach produced more accurate estimates of standing crop and FMC than did the multiple regression approach, although the gains were modest. The neural network models using day of year, canopy height, and NDVI as inputs explained 2.4% more of the variance in standing crop and 7.7% more of the variance in FMC than the corresponding regression models. However, the neural network models have substantially more complex model structure, which may make them more difficult for others to implement than the multiple regression approach. All of the neural network models developed here, along with a sample of the underlying data, are included in a Matlab file published as supplementary material with this paper. This will facilitate the use of the models by other researchers.

Some limitations of this study and the resulting models should be noted. First, there was a scale mismatch between the field of view for the radiometer, which covered approximately 0.79 m^2, and the quadrat size of 0.25 m^2 used for vegetation clipping. This scale mismatch likely inflated the error statistics for our models to some degree; thus, the actual model errors may be somewhat smaller than reported here. The larger field of view for the radiometer also helps to explain why substantially fewer sampling locations were needed for the nondestructive approaches to achieve a desired level of precision than for vegetation clipping. Second, the models developed here do not include time since fire as an input variable, although both standing crop and FMC are strongly influenced by time since fire. The exclusion of this variable was intentional because our objective was to design broadly applicable models and time since fire may be unknown outside of controlled experiments. Third, both types of models typically underestimated standing crop for levels above 600 g m^{-2} and underestimated FMC for levels above 150%. Therefore, the models are not well suited for use in grassland environments with standing crop or FMC levels above these thresholds.

Despite these limitations, the models developed here have been validated using data spanning nine large patches with different burn histories across three different pastures in 2 yr with distinctly different growing conditions. Given this relatively large variance in the underlying datasets, these models should be useful for nondestructive estimation of standing crop and FMC in other similar grassland environments, particularly when monitoring large, heterogenous areas for grazing management or wildfire preparedness. Instead of the multiband radiometer employed here, future studies should explore the potential of adopting smaller, less expensive, and easier-to-use handheld devices to estimate NDVI, or other relevant plant canopy measures, as inputs for estimating grassland standing crop and FMC. Newer technologies for automated in situ monitoring of canopy height and NDVI also appear to hold promise for nondestructive estimation of dynamic vegetation parameters to guide research and management.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rama.2018.01.001.

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