Estimating Above-Ground Biomass Measures on Semi-Arid Rangeland Using Remote Sensing

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Executive Summary

In this study, we sought to produce quantitative estimates of above ground biomass in south Texas rangeland using satellite remote sensing data. Above ground biomass (AGB) is a measurement of the weight of all organic matter above ground level and is frequently used to monitor grazing intensity, assess range health, and measure primary productivity of pastures. The most reliable methods for measuring AGB involve harvesting vegetation at multiple sample locations; however, this approach is time and labor intensive which inhibits biomass estimation over large areas. Satellite remote sensing data has the potential to overcome these limitations by providing accurate and repeatable measurements of ground conditions across large scales at high spatial resolutions. The objective of this study was to model the relationship between satellite remote sensing data, collected by optical and synthetic aperture radar sensors, and field measurements of biomass using linear regression techniques.

Samples of grass, forage, and total AGB were collected during a 4 day sampling campaign between July 21-25, 2020 on the Coloraditas Grazing and Research Demonstration Area (CGRDA) at the San Antonio Viejo Ranch near Hebbronville, Texas. Multiple vegetation indices — derived from Landsat 8 OLI imagery — and synthetic aperture radar (SAR) backscatter from Sentinel-1 imagery were used as dependent variables to build linear regression models to predict AGB values. Each of these individual variables were used as predictors in univariate models to estimate the weight of biomass samples. The highest performing optical variables were then combined with SAR backscatter into multiple linear regression (MLR) models to investigate whether a combination of both optical and SAR data improves prediction accuracy.

Our analysis found significant fits for several univariate models; however, all of these models displayed low R^2 values (0.10 – 0.53). The single variable which best predicted each biomass measurement was the Normalized Senescent Vegetation Index (grass R^2: 0.37, forage R^2: 0.53, total R^2: 0.44). The inclusion of SAR co-polarized (VV) backscatter data along with optical data improved

the predictive ability in MLR models (grass R^2: 0.40, forage R^2: 0.59, total R^2: 0.54). When tested on a subset of sample data, the highest performing MLR models achieved root mean squared errors of 107.75 kg/ha for total biomass, 123.60 kg/ha for forage biomass and 99.37 kg/ha for grass biomass.

Factors which might have negatively impacted these models include the presence of standing dead litter due to lack of recent grazing within the study area or the exclusion of woody biomass from our sampling design. Similar studies have reported limitations in the portability of such models over time and space which indicates that further use of the methods presented here should be accompanied by rigorous accuracy assessment. Additionally, these remote sensing variables may become more or less sensitive to ground conditions as vegetation phenology progresses throughout the year. Future investigation into the matter should seek to identify the combination of remote sensing data with the most predictive capacity at other times in the growing season. Furthermore, the techniques explored in this study are only applicable on areas with a low percent cover of woody canopy and composed of relatively homogeneous native pasture.

The findings of this study indicate that a combination of optical and SAR remote sensing data have a significant, yet limited, ability to estimate AGB in south Texas rangeland. More accurate estimates were produced for aggregated measures of biomass (forage and total AGB) when compared to individual components of the vegetation canopy (grass). This technique of AGB estimation could be used to assess the productivity of rangeland on an intra-annual basis or to compare production on inter-annual timeframes. These estimates can provide information to drive grazing management decisions and monitor range health over time.

Contents

1 Introduction

Rangeland comprises a large portion of the south Texas landscape where the predominate agricultural land use is livestock production, usually hand-in-hand with wildlife management. The semi-arid climate of the region leads to ranch acreages that are larger than the statewide average to accommodate the grazing requirements of large livestock operations (Foster, 2014). Sparse vegetation and frequent drought conditions present challenges for the adequate management of forage stocks. Palatable species of forage vegetation are sensitive to grazing pressure and proper stocking rates are needed to maintain optimal rangeland conditions (Everitt et al., 2006). The long-term monitoring of vegetative cover in arid regions, like south Texas, can be a critical tool for managing grazing intensity while providing early warning of deteriorating range conditions. The quantity of standing vegetation is one important indicator that can be used to assess the health of rangeland and is commonly measured as the weight of above ground biomass (AGB), which is a quantification of living vegetation above ground level. Measurements of AGB are taken using destructive or non-destructive techniques to collect samples in situ. Destructive biomass sampling involves the harvest of vegetation to acquire a weight, usually after drying the harvested vegetation to remove the influence of moisture on the samples. Non-destructive methods typically involve the use of allometric equations to associate measurements of plant or canopy characteristics to estimate the weight of biomass. These methods are practical for small areas; however, the time and resources required to accurately sample large areas of rangeland, such as those found in south Texas, can reduce their usefulness.

Satellite remote sensing has been proven to provide repeatable, large scale estimates of biomass in rangelands in a variety of environments (Anderson et al., 1993; Marsett et al., 2006; Mutanga and Rugege, 2006; Qi and Wallace, 2002; Wang et al., 2019). The high spatial resolution and continuous nature of remote sensing data can give range managers information about vegetation conditions across large areas. In this study, we attempt to estimate measures of various

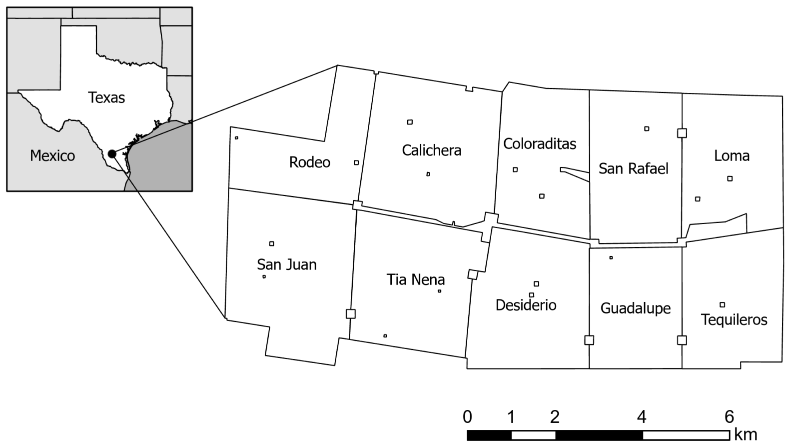

Figure 1: A map of the CRGDA pastures and the geographic location of the study area within the U.S. state of Texas. Adapted from Fern et al. (2018).

components of AGB using satellite remote sensing imagery. The goal of this study is to provide methods of monitoring range health at large scales for rangelands in south Texas. Here, we use field reference data, optical remote sensing imagery, and synthetic aperture radar data to fit linear regression models in order to predict AGB.

2 Methods

2.1 Study Area

Our study area was the Coloraditas Grazing Research and Demonstration Area (CGRDA), which is a 7,684 ha pasture complex located within the San Antonio Viejo Ranch, a historic ranching operation approximately 100 km northwest of McAllen, Texas (Figure 1). The landscape of the CGRDA is typical of the semi-arid Texas Tamaulipan thornscrub and coastal sand plain ecoregions, with woody vegetation and cacti interspersed among tallgrass prairie. The area is characterized by relatively level terrain at low elevations (less than 45 meters) above sea level, and sandy soils. This region is classified as an arid steppe with a mean annual precipitation of approximately 600 mm, and temperatures that range from 6° C in January to 36° C in August. In the month leading up to sampling (June 2020 — July 2020), a total of 43.18 mm of precipitation was measured by a nearby weather station, and less than 2 mm of precipitation was recorded in the week prior to sampling (SRCC, 2020). While originally established with a combination of rotational and continuous grazing systems, grazing had not occurred within the CGRDA in the two years preceding this study.

2.2 Ground Survey

A common issue with published methods for estimating biomass using remote sensing is a mismatch between the size of ground samples taken and the spatial resolution of satellite imagery being used to make predictions (Eisfelder et al., 2012). Our sampling scheme addressed this problem by systematically arranging several sample points within a larger plot to ensure plot data captured the spatial variability within in each pixel. Plots were placed in random locations within areas of homogeneous land cover and stratified proportionally among 4 distinct ecosites found in the study area. Regions of high woody vegetative cover were avoided to ensure that tree canopy did not influence the remote sensing pixel values or obscure the low lying vegetation, which was the target of this study.

Each plot consisted of a single north-south transect with 10 sample points distributed at regular intervals along the length of the transect (Figure 2). Transect starting locations were marked with a survey flag and loggers tape was used to measure 60 m along a magnetic north azimuth as measured by a compass. Survey flags were also used to mark the end point of the transect, as well as 4 intermediate points along the transect at 12 m intervals to be used as a visual reference for survey crews. Samples were taken at the start and end of the transect, while the remaining 8 samples were taken in pairs, offset to each side, at each 12 meter interval along the length of the transect. Our sampling was focused on herbaceous biomass and was broken down into categories of grass,

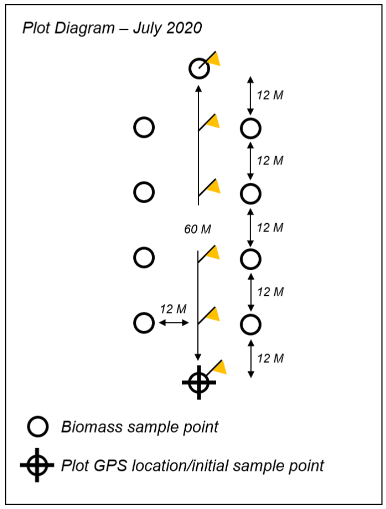

Figure 2: Diagram of plot structure used to collect biomass samples. Flags indicate visual reference markers used by sampling crews.

forb, and litter biomass. Grass biomass consisted of grass species including desiccated or senescent vegetation attached to the plant, forb biomass included all non-grass herbaceous flowering plants, and litter was considered to be all non-standing dead biomass. Prickly pear cacti (*Opuntia spp.*) frequently occur within the study area, but were excluded from sampling due to their significant contribution to biomass weight and disproportionately low spectral signature in satellite imagery (Todd et al., 1998). A destructive clip-and-weigh sampling technique was used to collect biomass measurements within 25 x 25 cm rigid plastic frames at each sample point. All above-ground biomass rooted within the frame was clipped at ground level, sorted, and placed in paper bags to be dried and weighed along with any litter which lay within the boundary of the frame. Plot-level measurements of AGB were calculated as the mean weight for each category of sample among all 10 sample points at each plot (Table 1).

2.3 Satellite Imagery and Preprocessing

One Landsat 8 Operational Land Imager (OLI) scene collected on July 17, 2020 with geographic coverage of the study area was acquired for analysis (Figure 3).

Table 1: Summary statistics of AGB measurements taken at 30 sample plots.

Biomass component	Min (kg/ha)	Max (kg/ha)	Mean (kg/ha)
Grass	101.6	460.3	264.9
Forbs	43.5	362.9	112.6
Litter	27.1	715.6	165.5
Forage	113.1	941.8	430.4
Total	187.3	985.3	543.1

The United States Geological Survey (USGS) provides this data as a terrain and atmosphere corrected product, accounting for errors associated with topography and atmospheric scattering. Pixel values of the Landsat imagery represented surface reflectance, which has been found to correlate better with AGB when compared to digital numbers (Samimi and Kraus, 2004). We also acquired synthetic aperture radar (SAR) data collected by the SEntinel-1 satellite on July 20, 2020 with geographic coverage of the study area (Figure 4). Sentenel-1 is an earth observation satellite operated by the European Space Agency which collects C-band SAR imagery at a 10 m resolution with a roughly 6 day revisit rate. Wang et al. (2019) found that inclusion of SAR data in linear regression models improved the estimation of leaf area index and AGB in pastures with homogeneous low-lying vegetation cover. For this study, we utilized the co-polarized (VV) backscatter band, which measures the intensity of energy reflected back to the sensor by targets on the earth's surface. Speckle noise present in the SAR imagery was reduced by applying a 3 pixel by 3 pixel moving window average filter. Pixel values of SAR data represented the backscatter coefficient in decibels (dB) in a logarithmic scaling.

Several spectral indices were calculated from the satellite imagery for use as predictors when modelling AGB (Table 2), along with the near infrared surface reflectance (band 5). Spectral indices use combinations of imagery bands to leverage the variation in radiometry among various surface features to improve target discrimination when using optical imagery. The Normalized Difference Vegetation Index (NDVI) is a commonly used spectral index that exploits the high reflectance of near infrared wavelengths and the relatively low reflectance of

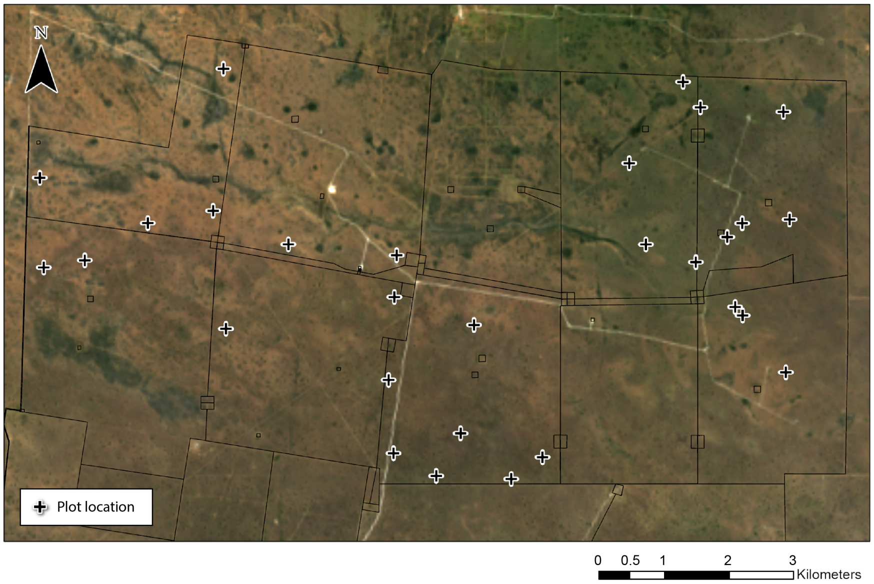

Figure 3: Landsat 8 OLI imagery of the study area, collected on July 17, 2020 and displayed in true color composite.

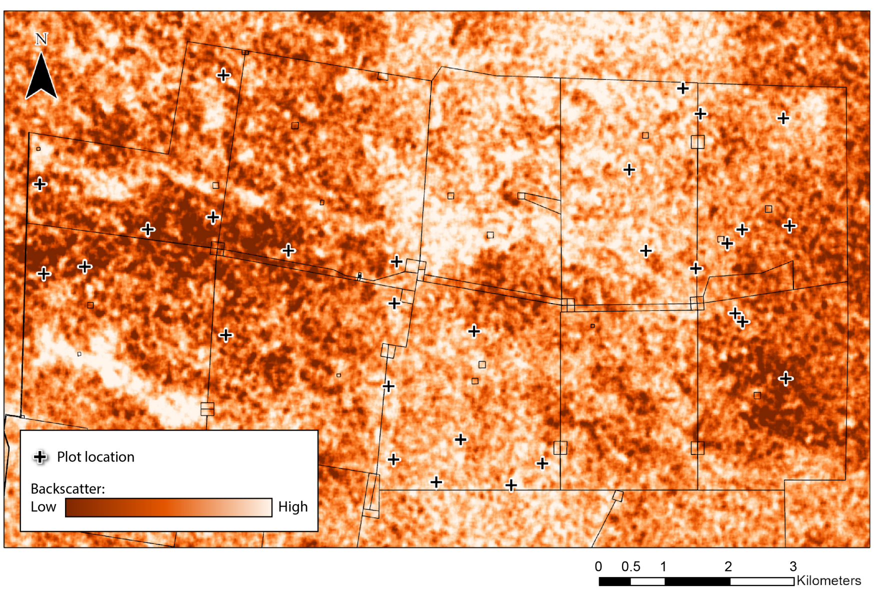

Figure 4: Sentinel-1 SAR imagery of the study area (VV backscatter), collected on July 20, 2020.

Table 2: Equations used to calculate vegetation indices.

Index	Formula	Source
NDVI	$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$	Rouse (1973)
OSAVI	$OSAVI = \frac{(NIR - RED)}{(NIR + RED + 0.16)}$	Rondeaux et al. (1996)
NSVI	$NSVI = \frac{(SWIR - RED)}{(SWIR + RED)}$	Qi and Wallace (2002)
MSAVI	$MSAVI = NIR + 0.5 - \sqrt{(2 * NIR + 1)^2 - 8(NIR - (2 * RED))}$	Qi et al. (1994)
TCW	$TCW = OLI2 * 0.1511 + OLI3 * 0.1973 + OLI4 * 0.3283 + OLI5 * 0.3407 + OLI6 * (-0.7117) + OLI7 * (-0.4559)$	Baig et al. (2014)

red wavelengths in photosynthesizing vegetation. This index takes the difference of the NIR and red bands and divides it by the sum of the same, providing a value ranging between -1 and 1 (Rouse, 1973).

Previous studies have found that soil reflectance can have a significant impact on the values recorded in imagery, especially in areas of sparse vegetation such as our study area. To account for the impact of soil background, we included the Optimized Soil Adjusted Vegetation Index (OSAVI), which uses a formula similar to NDVI with a correction factor for soil reflectance (Rondeaux et al., 1996). Fern et al. (2018) found that the OSAVI was able to produce vegetation coverage estimates of south Texas rangeland that were more accurate than those derived using NDVI. Senescent vegetation from previous growing seasons can degrade the correlation between AGB and spectral indices such as NDVI due to the increased proportion of visible reflection exhibited by non-photosynthetic vegetation. Qi and Wallace (2002) found that a spectral index derived using the red and SWIR wavelengths (Normalized Senescent Vegetation Index, NSVI) showed high correlations with AGB in rangeland with a high proportion of senescent vegetation. The NSVI was included in this study due to the presence of senescent vegetation throughout the study area at the time of sampling. The tasseled cap transformations of brightness (TCB), greenness (TCG), and wetness (TCW) were also included in this study (Baig et al., 2014). These are data transformations of pixel values from the visible and infrared bands of Landsat 8 imagery, and have been found to correlate with measures of standing crop in semi-arid rangeland (Moleele et al., 2001). The TCB transformation is sensitive to variations in total reflectance, while TCG is highly correlated with the quantity of photosynthetically active vegetation in a pixel; however, initial data exploration indicated highly non-normal distributions of these values, therefore the TCB and TCG were left out from further analysis to satisfy the assumptions of linear regression. The TCW is primarily sensitive to soil moisture and plant turgidity and has been found to be highly responsive to variations in green biomass when soil backgrounds are dry (Todd et al., 1998).

2.4 Statistical Analysis

During initial data exploration, we found that biomass values showed non-normal distributions which we addressed by applying a logarithmic transformation to meet the assumptions of linear regression. We held aside a random subset of the data (8 points) from model calibration to be used later for accuracy assessment. Weights of grass, forage, and total AGB were estimated using optical remote sensing variables (Landsat 8 imagery and vegetation indices) and SAR backscatter as predictors in ordinary least squares regression performed with R programming software (R Core Team, 2020). First, we took a univariate approach to modeling biomass by predicting grass, forage, and total AGB weights with each remote sensing variable. The R^2 values of each model were compared to assess how well each variable predicted biomass. Then, we took a multivariate approach that used the highest performing optical remote sensing variables and SAR backscatter as dependent variables in multiple linear regression to determine whether a combination of optical and SAR data improved biomass prediction. Again, we used R^2 values to compare the performance of each model, and the highest performing models were selected for further accuracy assessment. Model accuracy was assessed by predicting the subset test data using the top four performing models for each biomass component (grass, forage, and total) to determine how well each model was able to estimate points not included in the calibration dataset. We used the root mean squared error of these predictions to

Table 3: Univariate regression model results.

Biomass Component	Predictor	R^2	P
Grass	NSVI	0.37	<0.05
	SAR	0.30	<0.05
	Band 5	0.21	<0.05
	NDVI	0.21	<0.05
	MSAVI	0.18	<0.05
	TCW	0.15	<0.05
	OSAVI	0.15	<0.05
Forage	NSVI	0.53	<0.05
	Band 5	0.38	<0.05
	SAR	0.34	<0.05
	NDVI	0.23	<0.05
	MSAVI	0.19	<0.05
	TCW	0.17	<0.05
	OSAVI	0.12	<0.05
Total	NSVI	0.44	<0.05
	SAR	0.40	<0.05
	NDVI	0.29	<0.05
	Band 5	0.26	<0.05
	MSAVI	0.26	<0.05
	TCW	0.23	0.056
	OSAVI	0.19	0.066

evaluate the accuracy of model outputs as compared to corresponding ground reference data.

3 Results

Univariate models showed weak relationships between measures of grass biomass and remote sensing data, explaining between 15% to 37% of the variation in AGB (Table 3). The dependent variables which produced the closest fit for grass biomass were NSVI and SAR backscatter with R^2 values of 0.37 and 0.30, respectively. The fit of univariate models improved when predicting forage biomass which incorporated the weight of forbs along with grass into the independent variable. Again, NSVI showed the best fit when predicting forage biomass, explaining 53% of the variation in ground measurements. Univariate models of total biomass appeared to have relatively lower predictive capacity,

Table 4: Multivariate regression model results.

Biomass Component	Predictors	R^2
Grass	Band 5 + SAR	0.42
	NSVI + SAR	0.41
	NDVI + SAR	0.25
	MSAVI + SAR	0.25
Forage	Band 5 + SAR	0.59
	NSVI + SAR	0.58
	NDVI + SAR	0.27
	MSAVI + SAR	0.27
Total	NSVI + SAR	0.54
	Band 5 + SAR	0.53
	NDVI + SAR	0.34
	MSAVI + SAR	0.34

only explaining up to 44% of variation in AGB at best.

Multiple linear regression models showed improvement over univariate models across all three biomass measures (Table 4). The greatest increase in R^2 was seen in the total biomass model, which explained 54% of the variation in observed values (increase of 10%) when a combination of NSVI and SAR were used as dependent variables. A combination of band 5 values and SAR backscatter were able to explain 59% of variation in forage biomass sample data. Multiple linear regression models of grass biomass showed weaker relationships in comparison to those of forage and total biomass with a maximum R^2 value of 0.42. When the top performing models were used to predict a subset of sample points, the RMSE of the predictions matched the pattern seen in the R^2 values reported in the previous steps (Fig. 5).

4 Discussion

The high correlation of AGB measures with the NSVI indicates that the short-wave infrared bands of Landsat imagery captures information about the vegetation canopy more accurately than the near infrared band and associated indices (NDVI, OSAVI, and MSAVI). This agrees with the findings of Qi and

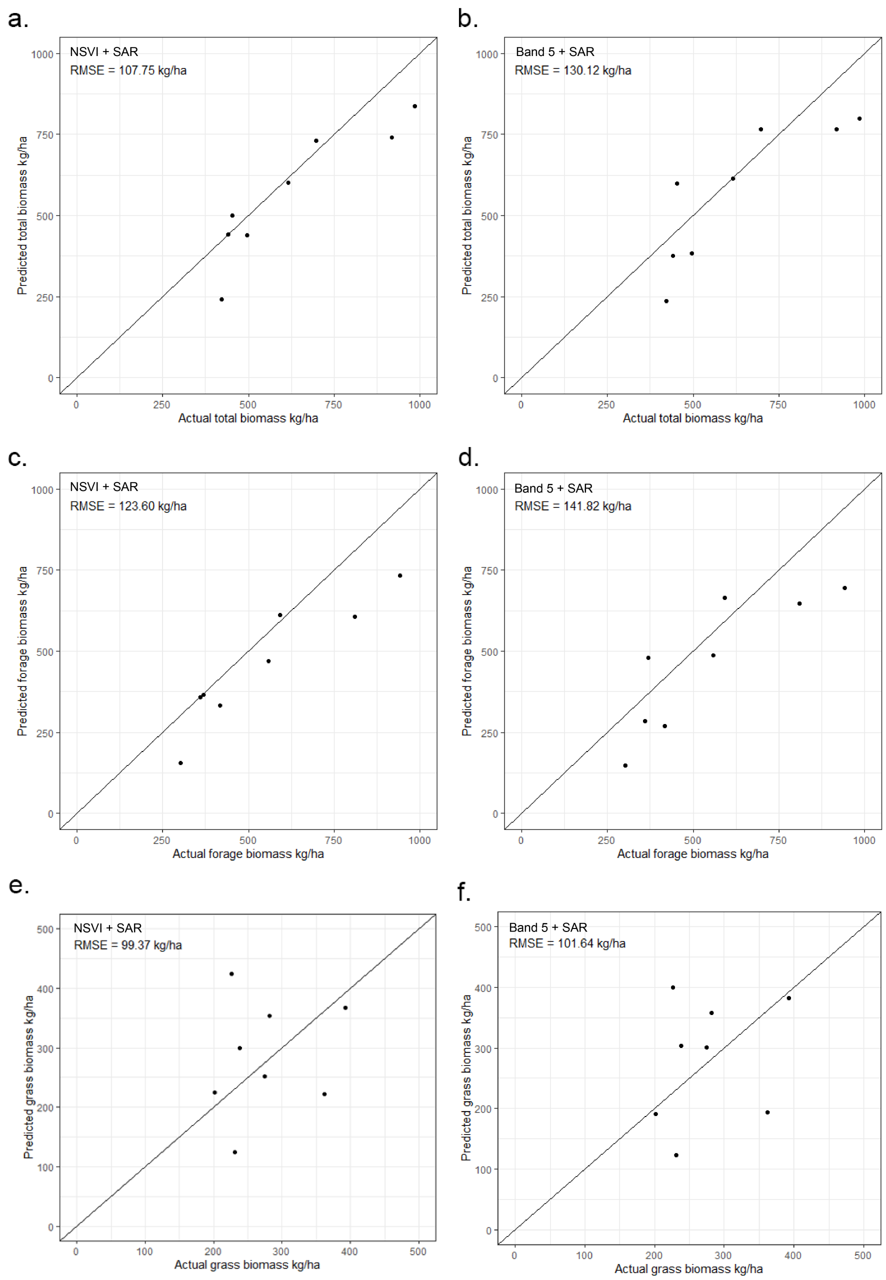

Figure 5: Scatterplots of predicted and measured biomass (total: a, b; forage: c, d; and grass: e, f) and RMSE of predictions.

Wallace (2002), which found that SWIR bands are able to represent the senescent vegetation better than indices which rely on the near-infrared band. A common constraint when using remote sensing data to estimate biomass is limited portability of models over time or space, and it is likely that this effect is very dependent on the phenology of target vegetation or the composition of the canopy (Eisfelder et al., 2012). Therefore, the close association between AGB and NSVI may reduce at other points in the growing season as vegetation green up occurs, or in other ecosites with dissimilar vegetative cover. Increased grazing activity may also degrade the relationship as green vegetation is consumed by livestock instead of contributing to the dead litter or senescent vegetation in the following growing season (Todd et al., 1998).

The high performance of models that incorporated SAR data indicates that co-polarized backscatter is able to quantify key characteristics of the vegetation canopy which correlate with AGB. Wang et al. (2019) found that SAR performed poorly when estimating biomass in areas of low vegetative cover due to the influence of the soil background, while optical data became saturated in high biomass areas. Models which combined the two data types were able to predict biomass better than each variable separately. The density of low-lying vegetation found in south Texas native pastures can vary drastically, and the improved performance observed in our multivariate models agrees with these findings.

5 Conclusion

The semi-arid climate of south Texas and historical overgrazing requires livestock operations to carefully manage their pastures for optimal performance. Land stewards benefit from reliable measurements of the quantity of vegetation which can be used to guide stocking rates and monitor range health over time. The results of this study indicate a limited, yet promising, ability to estimate the weight of AGB within native pasture using satellite remote sensing data. We also found that a combination of optical and SAR backscatter in multiple linear regression models improved the accuracy of AGB estimates. These models were able to predict the total mass of AGB, as well as the weight of grazing specific components (grass and total forage weights), which could be used to evaluate grazing intensity, monitor pasture productivity, and observe trends in range health over time.

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