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Suitability of NDVI and OSAVI as estimators of green biomass and coverage in a semi-arid rangeland

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ABSTRACT

Rangelands are often too large and inaccessible to determine biomass accumulation and vegetation cover by ground surveys alone, particularly in semi-arid regions where productivity per unit area is typically low and highly variable. Thus, the development of remote sensing derived spectral indices have been of particular interest to rangeland managers as a more cost-effective means of measuring the characteristics, biomass, and extent of vegetation. The Normalized Difference Vegetation Index (NDVI) is the most widely used spectral vegetation index (VI) by ecologists and agriculturalists today. However, regions with sparse vegetation or soils that generate high reflectance values (e.g., dry sandy soils) can severely hinder the reliability of the NDVI as an accurate estimator of green biomass, saturate remote sensors or produce biased estimates of green biomass and vegetative cover. The Optimized Soil Adjusted Vegetation Index (OSAVI) is a newly formed alternative that can accommodate greater variability due to high soil background values. We evaluated the suitability of the NDVI and OSAVI as potential estimators of green biomass and vegetative coverage in a semi-arid rangeland in south Texas. We compared coverage estimates of herbaceous, bare-ground, and woody vegetation calculated from classified satellite images stacked with either an NDVI or OSAVI band to those from traditional ground surveys. OSAVI-derived coverage estimates of herbaceous and woody vegetation did not significantly differ from those produced by ground surveys in 2015. However, NDVI-based estimates for woody vegetation, as well as bare ground, did differ significantly from estimates generated from ground surveys (p = 0.012, 0.018). In 2016, the OSAVI-derived estimates for all three land cover classes were not significantly different than those produced by ground surveys. Our results suggest the OSAVI to be the most appropriate VI-based estimator of green biomass and vegetative coverage in the semi-arid regions of southern Texas.

1. Introduction

Although spectral vegetation indices have a long history of use by remote sensing scientists, they are an increasingly popular tool used by agriculturalists and rangeland ecologists (Curran et al., 1992; Henebry, 1993; Wabnitz et al., 2008). Determining biomass accumulation and vegetation cover of rangelands using ground surveys can be time consuming and costly, particularly on large, semi-arid regions where productivity per unit area is typically low and highly variable from year to year. Thus, the development of remote sensing derived spectral indices have been of particular interest to rangeland managers as a more cost-effective means of measuring the characteristics, biomass, and extent of vegetation (Eisfelder et al., 2012).

The Normalized Difference Vegetation Index (NDVI) is the most widely used spectral vegetation index (VI) by ecologists and agriculturalists today (Horning et al., 2010; Yagci et al., 2014; Lee et al., 2016). Similar to most VIs, the NDVI transforms reflectance measurements from the reflectance peak of vegetation in the near-infrared (NIR) and red wavelength ranges where chlorophyll absorbs light energy for photosynthesis. The purpose of this two-band design is to reduce variability caused by reflectance of the soil background, illumination, and view angle variation. However, regions with sparse vegetation or soils that generate high reflectance values (e.g., dry sandy soils) can saturate remote sensors or produce biased estimates of green biomass and vegetative cover (Huete et al., 1997; Nicholson and Farrar, 1994). Remote sensing scientists have addressed this through formulating new spectral vegetation indices that can accommodate greater variability due to soil reflectance (e.g., Soil Adjusted Vegetation Index, SAVI; Optimized Soil Adjusted Vegetation Index, OSAVI). Although the NDVI is still used for estimating biomass and coverage in areas with wildly varying vegetation types, its use in semi-arid rangelands is becoming increasingly suspect especially in regions with sandy soils (Bowers and

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Hanks, 1965; Gu et al., 2008).

The Rio Grande Plains, or "brush country", encompasses the Coastal Sand Plain, Tamaulipas Thornscrub, and Lower Rio Grande Valley ecoregions of Texas (Omernik, 1987). The region, as a whole, is primarily managed for agricultural use. However, in the smaller, Tamaulipas Thornscrub and Coastal Sand Plan regions, wildlife based management often outpaces agricultural interests. Frequent and reoccurring drought presents unique challenges to cattle ranching in this region as naturally available vegetation is often sparse (Taylor, 2014). Thus, landowners are charged with the task of developing profitable management systems that balance the needs of sustainable cattle and/or wildlife enterprises as well as those of sensitive wildlife populations in the presence of frequent and reoccurring drought. Accurate and cost-effective vegetation monitoring is crucial to any effective rangeland management strategy and spectral VIs can provide a valuable tool towards reaching this end. However, the use of the NDVI in this region is questionable, at best, due to the high sand content of the soils and sparse vegetation (Eastwood et al., 1997; Elmore et al., 2000; Todd and Hoffer 1998).

Here, we evaluate the suitability of the NDVI and OSAVI as potential estimators of green biomass and vegetative coverage in a semi-arid rangeland in south Texas. We compared coverage estimates of herbaceous, bare-ground, and woody vegetation calculated from classified satellite images stacked with either an NDVI or OSAVI band to those from traditional ground surveys.

2. Methods

2.1 Study area

The Coloraditas Grazing Research and Demonstration Area (CGRDA) is a 7684-ha area located on the 60,000-ha San Antonio Viejo Ranch (SAV). SAV is one of six properties of the East Foundation that are managed as a living laboratory to support wildlife conservation and other public benefits of ranching and private land stewardship. The CGRDA is representative of south Texas rangeland ecosystems and encompasses the Coastal Sand Plain and Texas-Tamulipan Thronscrub ecoregions. Low-growing woody plants, dense shrubs (*Prosopis glandulosa*, *Acacia greggii*, *Celtis ehrenbergiana*, *Colubrina texensis, Aloysia gratissima, Lantana urticoides*), and cacti (*Opuntia engelmannii* var. *lindheimeri*, *Opuntia leptocaulis*) dominate the vegetation in this area. The CGRDA is comprised of 10 pastures (Fig. 1) each assigned to 1 of 4 cattle grazing systems. Four pastures are assigned to a continuous grazing system with 2 pastures maintained under a high stocking rate (1 Animal Unit [AU]/14 ha) and 2 pastures under a moderate stocking rate (1 AU/20 ha). Six pastures are assigned to a rotational system with 3 pastures, 1 herd maintained under the high stocking rate and 3 pastures, 1 herd maintained under the moderate stocking rate. Grazing was deferred on all pastures for two years prior to the onset of cattle grazing in December 2015. We compared pre- and post-grazing vegetation cover estimates from ground surveys.

2.2 Ground surveys

We collected vegetation composition and structure data from 141 permanent 20-m transects each October in 2015 and 2016. We allocated transects proportional to the area of ecological sites that occur in each pasture using stratified sampling resulting in 12–16 transects per pasture (Bonham, 2013). Sample size for belt transects was determined by a power analysis with an 80% chance in detecting a 20% change in canopy cover at $P \leq 0.05$. Detecting a 20% change in bare ground required the highest number of transects out of the 4 measurements, therefore, we used this as the minimum number of transects placed in each pasture.

We marked each transect start with a t-post and collected data in a random, predetermined direction (N, S, E, W). On each transect we sampled 5, 20 × 50 cm quadrats (5 m spacing) randomly placed at either 0, 0.5, 1, 1.5, 2, or 2.5 m from the left side of the tape and facing away from the transect start. The specifics for transect direction and quadrat spacing start remained constant for each transect over the course of the study.

At each transect, we collected percent cover of woody, herbaceous, litter, and bare ground. We defined woody canopy cover as the portion of foliage cover projected on the ground (Bonham, 2013). We collected woody canopy cover along each of the 20 m transects by recording the amount of the ground (in centimeters) covered by woody plant materials (leaves and branches) and succulent (cacti) that intercepted the line transect by species (Canfield, 1941; Higgins et al., 2012). If a gap in the canopy exceeded 0.5 m for an individual, we recorded separate cover measurements. We calculated percent canopy cover by summing the intercept measurements for an individual species, dividing by total line length and converting to a cover percentage. We calculated total percent cover by adding cover percentages for all species, which may exceed 100% when overlapping canopies by different species are recorded (Coulloudon et al., 1999).

We defined herbaceous cover as the non-woody vegetation, such as grasses and forbs, projected onto the ground (Bonham, 2013). We defined bare-ground as the amount of soil that is not covered by any type of vegetation (Holecheck et al., 2011). Within each quadrat, we measured percent canopy cover by 4 functional groups (grass, forb, bare ground, litter ≤ 100%) in 5% increments, this included increments of 1% for coverages < 5%. (Higgins et al., 2012). When woody or succulent cover was rooted within the frame, we made note of percent cover, species, and abundance. For the purpose of this analysis, we combined grass and forb cover into herbaceous cover and litter and bare ground into bare ground cover.

2.3 Imagery processing

We conducted a series of processing functions using imagery captured during the same growing season as when ground surveys took place (summer of 2015 and 2016) (Fig. 2). Two Landsat 8-OLI tiles (< 6% cloud cover) that encompassed the study area were acquired (courtesy of U.S. Geological Survey) and processed in ENVI 5.1 (NASA Landsat Program, 2015, 2016). We corrected for atmospheric conditions and converted the original image format of Digital Numbers (DN) to radiance and then surface reflectance. Each image was first resized to the rectangular extent of the LC pasture complex and then extracted by the study area mask in ESRI ArcGIS ArcMap 10.5. Both extracted images (2015 and 2016) were then spatially subset by bands 2–5 corresponding to Landsat 8-OLI band designations: blue, green, red, and NIR. Bands were stacked and two vegetation indices were calculated per image using the band math tool in ENVI 5.1. NDVI was calculated according to the standard formula [(NIR-Red)/(NIR + Red)] in which the drop in reflectance between the Near-Infrared (NIR) band and Red band is divided by the increase in reflectance. This creates index values between −1 and 1 (Rouse et al., 1973). We then stacked the NDVI as a band on the NIR-RGB image for, both, 2015 and 2016. Similarly, the OSAVI was calculated using ENVI's band math tool using the standard formula [(NIR-Red)/(NIR + Red + 0.16)] and stacked as a band on the NIR-RGB image for, both, 2015 and 2016. Based on the Soil Adjusted Vegetation Index (SAVI), this VI uses a reflectance constant of 0.16 to adjust for high background reflectance (e.g., areas with sparse vegetation and high soil reflectance) (Rondeaux et al., 1996; Ren et al., 2018).

We classified each VI-NIR-RGB stacked image using Maximum Likelihood supervised classification into three land cover classes: herbaceous, woody, and bare-ground. We calculated statistics for each class to estimate land cover coverage and performed an accuracy assessment for each classified image using ground truth points collected from ground surveys. We compared 2015 and 2016 classification accuracy (as a function of overall accuracy, Kappa coefficient, and producer's accuracy) and coverage estimates derived from VI-NIR-RGB

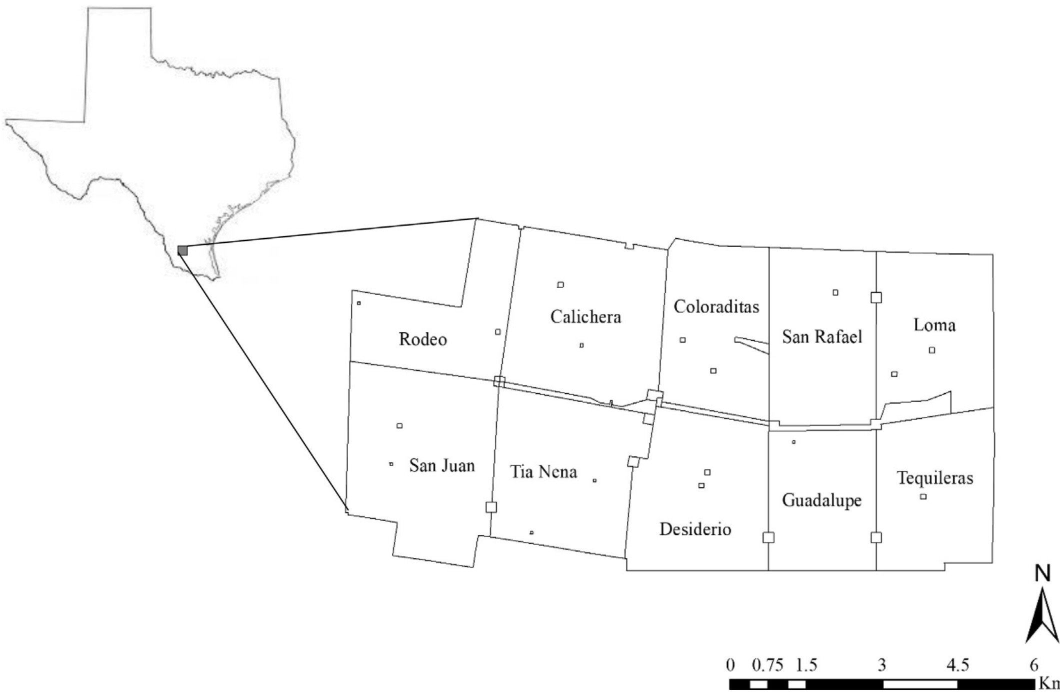

Fig. 1. Study area comprised of 10 pastures located on the San Antonio Viejo (SAV) Ranch of the East Foundation in south Texas. Combined, all named pastures constitute the Coloraditas Grazing Research and Demonstration Area (CGRDA).

stacked images for the CGRDA and per pasture. We then also compared land cover (%) change in coverage between the two years for each class (herbaceous, woody, bare). Coverage estimates derived from VI-NIR-RGB images were also compared to those generated using ground survey methods for both 2015 and 2016 using paired Student's t-tests.

3. Results

3.1 Image classification accuracy

For both 2015 and 2016 images, stacking the OSAVI produced a higher overall classification accuracy than stacking the NDVI (2015: 89.87% and 89.73%; 2016: 95.87% and 95.33%, respectively) (Table 1). Producer's accuracy within each land cover class was also higher in classified images stacked with OSAVI rather than NDVI.

Within each year, accuracy varied among land cover classes but woody classification accuracy was consistently higher in both VI-stacked images (2015: 88.4% and 90.8%; 2016: 96.4% and 97.6%, respectively). OSAVI- and NDVI-stacked classifications demonstrated the lowest accuracy for herbaceous cover in both years.

3.2 Coverage estimates

Herbaceous coverage estimates derived from image classification did not significantly differ from those derived from ground surveys for 2015 (NDVI + Ground survey: $p = 0.83$; OSAVI + Ground survey:

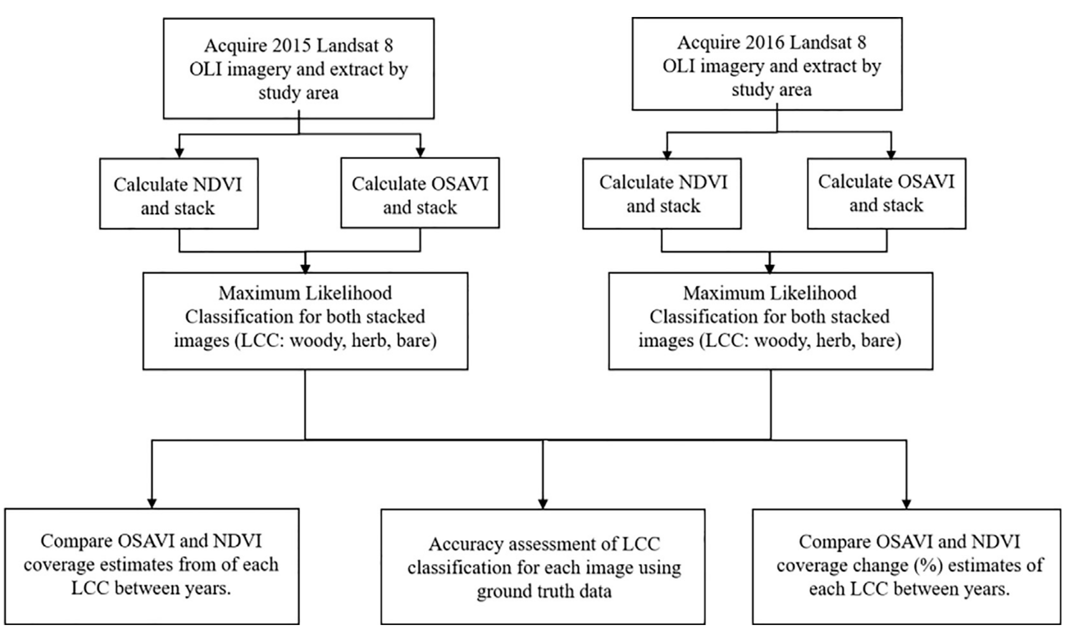

Fig. 2. Outline of processing workflow for this study.

Table 1
Accuracy assessment results for Maximum Likelihood classifications using NIR-RGB images of the CGRDA stacked with either NDVI or OSAVI vegetation indices for 2015 and 2016. Producer's accuracy for each land cover class is also reported per classification and year. *K* represents the kappa coefficient for each classification accuracy.

2015		Overall accuracy (%)	*K*	Class (producer's) accuracy (%)		
				Herbaceous	Woody	Bare
	NDVI	89.73	0.85	89.20	88.40	91.60
	OSAVI	89.87	0.85	86.80	90.80	92.00
2016						
	NDVI	95.33	0.93	93.60	96.40	94.80
	OSAVI	95.87	0.94	96.00	97.60	95.20

Table 2
Resulting *p* values of paired Student's t-tests for estimates of herbaceous, woody, and bare coverage in the CGRDA in 2015 and 2016. VI-derived coverage estimates (OSAVI and NDVI) are compared to those derived from traditional ground surveys. GS = Ground Survey; *Denotes significance.

	2015			2016		
	Herbaceous	Woody	Bare	Herbaceous	Woody	Bare
NDVI:GS	0.83	*0.012**	*0.018**	*0.0035**	0.73	*0.02**
OSAVI:GS	0.66	0.051	*0.022**	0.072	0.83	0.52

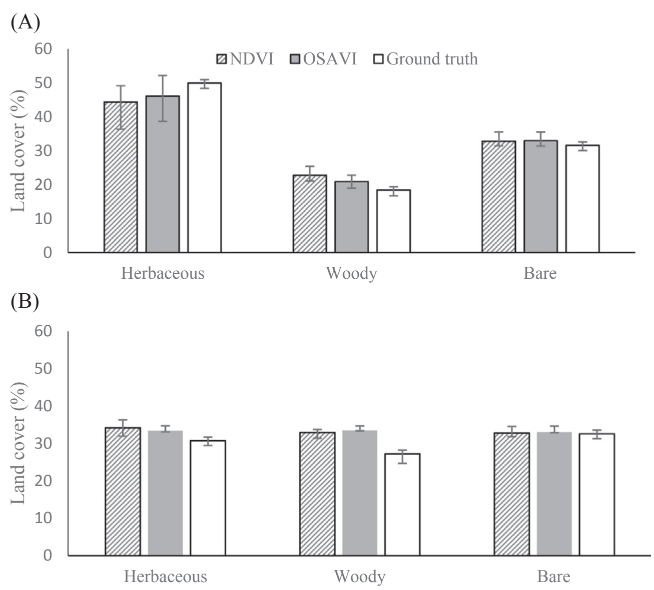

Fig. 3. Coverage estimates for 2015 (A) and 2016 (B) for the full extent of the CGRDA for each land cover class (herbaceous, woody, and bare) as derived from NIR-RGB imagery classification (stacked NDVI or OSAVI) and calculated from ground surveys. Error bars included in ground truth values represent standard error within each class. Error bars included in NDVI and OSAVI results represent omission error (upper limit) and commission error (lower limit) of the classified image for each land cover class.

$p = 0.66$; Table 2). However, coverage estimates for herbaceous vegetation generated using the NDVI were significantly different than those derived from ground surveys post-grazing, in 2016 ($p = 0.0035$). Estimates of woody vegetation coverage derived from the NDVI also differed significantly from those produced by ground surveys in 2015 ($p = 0.012$). Woody vegetation coverage estimates produced by both VIs did not significantly differ from ground survey estimates for 2016. Both NDVI- and OSAVI-derived coverage estimates for bare ground in 2015 differed significantly from bare ground coverage estimates produced by ground surveys ($p = 0.018$ and 0.022, respectively). However, OSAVI-based coverage estimates of bare ground in 2016 did not significantly differ from those produced by ground surveys ($p = 0.52$). Classification derived coverage estimates for 2015 held considerably more error than those for 2016, particularly within the herbaceous land cover class (NDVI: 4.79% omission error, 7.9% commission error; OSAVI: 6.1% omission error, 7.5% commission error; Ground survey: SE = 1.5; Fig. 3).

3.3 Estimating land cover change

Between 2015 and 2016, ground survey methods estimated a −12.7% change in herbaceous cover and 8.32% change in woody cover across the full extent of the CGRDA. NDVI-based classification produced similar estimates (−10.18% and 10.19%, respectively). OSAVI-based classification also produced similar estimates (−12.7% and 12.6%) but overestimated the increase in woody coverage. Although ground survey methods estimated a 5.9% change in bare coverage, both NDVI- and OSAVI-based classification failed to estimate any measurable change in bare-ground cover between 2015 and 2016 (< 1%).

Land cover change estimates per pasture varied considerably between imagery-based and ground survey-based methods (Fig. 4). Per pasture, NDVI-based classification tended to overestimate changes in herbaceous and woody coverage and underestimate changes in bare-ground coverage. In contrast, OSAVI-based classification tended to underestimate changes in woody and bare-ground coverage and estimate changes in herbaceous cover with reasonable accuracy.

4. Discussion

Our results suggest the OSAVI to be the most appropriate VI-based estimator of green biomass and vegetative coverage in the semi-arid regions of southern Texas. OSAVI-derived coverage estimates of herbaceous and woody vegetation did not significantly differ from those produced by ground surveys in 2015. The NDVI-based estimates for woody vegetation, as well as bare ground, did differ significantly from estimates generated from ground surveys. In 2016, the OSAVI-derived estimates for all three land cover classes were not significantly different than those produced by ground surveys. In contrast, the NDVI-based coverage estimates of herbaceous vegetation and bare ground differed significantly from estimates generated for ground surveys. In comparison to estimates generated by traditional ground survey methods, the OSAVI-based classification produced statistically similar coverage estimates for herbaceous and woody vegetation in both years.

Estimates varied per pasture, particularly for bare-ground coverage. Coverage estimate and classification accuracy was generally lower in 2015 (pre-grazing) than 2016 (post-grazing), likely due to the higher relative abundance of dried leaf litter and standing senesced plants, since the elevated visible reflectance exhibited by non-photosynthetic vegetation can distort the contrast between the visible and NIR reflectance (Todd et al., 1998). Both VIs also had the lowest classification accuracy for the bare-ground pixel class. The challenge of spectrally identifying bare-ground can be also attributed to the presence of organic litter material or senesced plants (Todd et al., 1998). Additionally, the bare-ground pixel class we classified here, represents areas absent of herbaceous or woody vegetation. Thus, this class could potentially include materials ranging from bare rock to fine sand or soil, all of which would produce differing spectral signatures. These issues can be easily addressed by a finer separation in bare-ground Regions of Interest (ROIs) in the initial classification or a post-processing mixed pixel analysis (MPA). However, for most rangeland managers, monitoring changes in herbaceous and woody cover remain the priority in assessing rangeland productivity (Qi et al., 2002; Prince and Tucker, 1986). Although soil moisture would not have directly affected vegetation indices due to the two-band design (i.e., using the drop in reflectance between NIR and red bands rather than raw reflectance

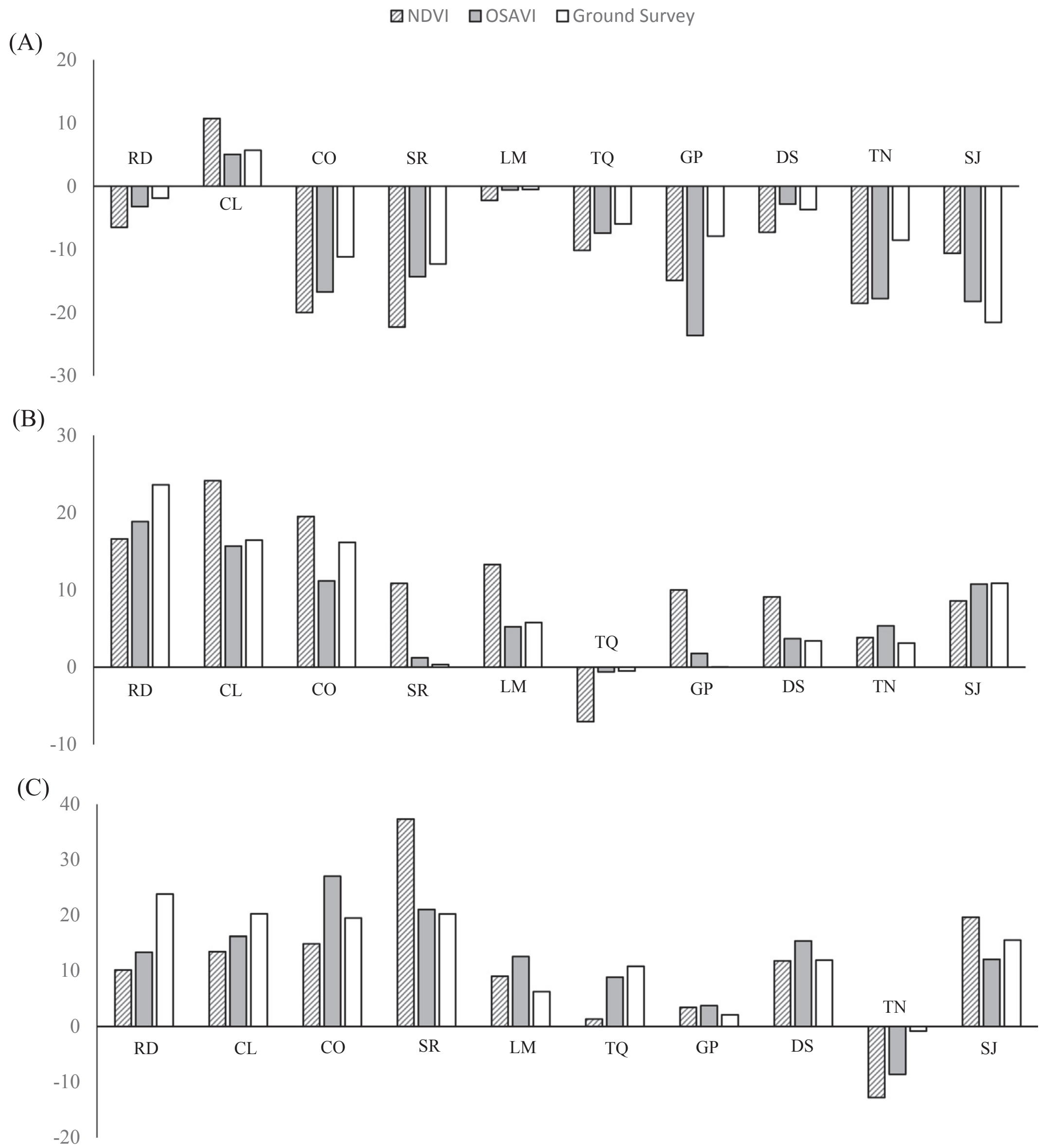

Fig. 4. Land cover change (%) for each land cover class (A = herbaceous, B = woody, and C = bare) between 2015 and 2016 per individual pasture of the CGRDA as derived from NIR-RGB imagery classification (stacked NDVI or OSAVI) and calculated from ground surveys. Pasture abbreviations used: Rodeo = RD, Calichera = CL, Coloraditas = CO, San Rafael = SR, Loma = LM, Tequileras = TQ, Guadalupe = GP, Desiderio = DS, Tia Nena = TN, San Juan = SJ.

values), variable precipitation could have contributed to the error in VI-based coverage estimates indirectly through temporary succulence of vegetation or the removal of dust or sand from green, photosynthetic leaf area. At a slightly higher wavelength (1.57–1.65 μm) the Short-wave Infrared (SWIR) band is especially sensitive to soil moisture content and may be significant in future studies involving biomass estimates in semi-arid rangelands (Harris and Asner, 2003; Jiapaer et al., 2011).

In agreement with several existing studies, the accuracy of both VIs in estimating herbaceous and woody coverage pre- and post-grazing demonstrate the suitability of these remotely sensed products in monitoring vegetative changes semi-arid, grazed rangelands (Diouf and Lambin, 2001; Lyon et al., 1998; Anderson et al., 1993). We suggest, however, that in south Texas rangelands, the OSAVI should be used preferentially as it accommodates the high levels of soil background variability found in semi-arid areas better than the NDVI. Vegetation indices are powerful alternatives to traditional ground survey methods for monitoring rangeland productivity and health since free-use satellite data are widely available and generating vegetation indices (and other remotely sensed products) is less time consuming than traditional vegetation sampling techniques on-foot. The OSAVI, then, can be a valuable tool for rangeland managers since its superior performance as an estimator of green biomass and vegetative coverage can provide an accurate and cost-effective, means of monitoring herbaceous changes across large, remote areas. This, more sensitive index, allows managers and rangeland ecologists to quantify long-term changes in vegetation condition and rangeland production under varying management regimes or during periods of recurring drought.

Accurate, remotely sensed estimates of vegetative biomass and coverage grant managers the tools to make quick and informed decisions regarding rangeland management (e.g., the duration of safe grazing seasons, stage of vegetative development, annual effects of weather on cattle forage, effects of grazing on plant succession) (Todd et al., 1998; Richardson et al., 1982). As the human population and demand for agriculture increase, rangeland ecologists are charged with the task of managing larger and more complex operations. The growing body of remotely-sensed data and derived products provide new tools and techniques to monitor vegetative changes in semi-arid rangelands.

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