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TECHNICAL COMMUNICATIONS

Relating Biophysical Parameters of Coastal Marshes to Hyperspectral Reflectance Data in the Bahia Blanca Estuary, Argentina

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ABSTRACT

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Salt marshes occupying the tidal fringe of estuaries and protected coasts provide valuable ecosystem services, and remote sensing is a powerful tool for their large-scale monitoring. However, in order to apply remote sensing techniques to evaluate the ecological state of salt marshes, a deeper understanding is needed about the interactions between field biophysical parameters and the sensor's reflectance. The main objective of this work is to analyze and quantify the influence of different biophysical parameters characterizing stands of *Spartina alterniflora* marshes in the Bahia Blanca Estuary, Argentina, on their spectral response. Spectral reflectance at high resolution was measured in *S. alterniflora* canopies under natural conditions, manipulating standing biomass by means of successive harvestings. Reflectance data were acquired using a FieldSpec® spectroradiometer, which measures in the visible, near-infrared, and shortwave-infrared spectral bands. Based on these reflectance data, spectral indices such as the normalized difference vegetation index (NDVI) were calculated for each biomass condition. Biomass, leaf area index (LAI), percent canopy cover (PCC), water content, and soil properties were also evaluated. LAI, PCC, and biomass were positively correlated between each other. As a general trend, as biomass decreased, absorption in red wavelengths decreased and reflectance in near-infrared increased. Several indices explained the variability in LAI, biomass, and PCC. For example, $NDVI_{Rouse}$ had a positive regression with PCC ($R^2 = 0.80$, $N = 75$) and LAI ($R^2 = 0.67$, $N = 75$). Results indicate that LAI, biomass, and PCC of *Spartina alterniflora* could be accurately determined from spectral data.

ADDITIONAL INDEX WORDS: *Coastal marshes, spectral indices, remote sensing, biomass, LAI, canopy cover, biophysical parameters, Spartina alterniflora.*

INTRODUCTION

Coastal wetlands provide widely recognized ecosystem services. For instance, salt marshes have been proven to act as effective storm buffers, as well as nutrient and fine sediment sinks, and these functions translate into valuable services such as shoreline protection and improvement of estuarine water quality (Mitsch and Gosselink, 1993). Because functions and values depend on the ecological integrity of coastal wetlands (Bedford and Preston, 1988; Brinson, 1988; Daiber, 1986), there is a growing interest in using environmental indicators to quantitatively determine changes in the health of coastal ecosystems (Klemas, 2001).

Landscape-level indicators (OECD 1998, 1999, 2001; O'Neill *et al.*, 1988, 1997) become particularly important as we shift to larger temporal, spatial, and organizational scales in order to study and compare the cumulative effects of coastal ecosystem degradation over entire landscapes and regions (Haines-Young, Green, and Cousins, 1993). There are important landscape-level environmental indicators that can be extracted from remotely sensed data, such as changes in the size and configuration of coastal habitats and vegetation cover. These indicators can be related to estuarine biodiversity and condition (Arnold and Gibbons, 1996; Klemas, 2001; USDA Forest Service, 1996), allowing considerable savings of time

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and money, especially if large coastal areas need to be monitored (Klemas, 2001).

One commonly used and accepted parameter for evaluating ecosystem condition is biomass and/or net primary productivity. Both terms refer to the dry weight of plants (expressed as grams dry weight per square meter for the biomass and usually as per year for the productivity). Rapid changes in biomass and primary production may be signs of illness or profound disease in an ecosystem, where change can include both accumulation and loss of biomass (Jensen *et al*., 1998). However, field estimations of these indicators are particularly complicated in the case of salt marshes, given their inherent heterogeneity and the presence of large spatial gradients. To overcome the problems of direct observation, broad-scale remote monitoring techniques are increasingly being used (Vis, Hudon, and Carignan, 2003). Besides biomass, parameters such as percent cover (Heege, Bogner, and Pinnel, 2004; Pinnel, Heege, and Zimmermann, 2004) and leaf area index (LAI) (Dierssen and Zimmerman, 2003) can also be estimated through the use of remote sensing, providing a tool for quantifying biophysical and ecological parameters describing macrophyte stands, which often are required inputs to ecosystem models (Silva *et al*., 2008).

Moreover, the use of remotely sensed images allows multitemporal studies and provides comprehensive information from surrounding areas (Vis, Hudon, and Carignan, 2003).The next generation of optical Earth-observing satellites includes sensors having many additional spectral channels and higher spatial resolution, which will offer new opportunities to provide information about site conditions. With the advance of sensor technology and processing techniques, vegetation characteristics such as species composition, LAI, biomass, absorbed photosynthetically active radiation, and even chemical composition can be determined by analysis of radiometric data (Peñuelas *et al*., 1993; Tilley *et al*., 2003). To take advantage of these technologies, a deeper understanding is needed about the interaction between field biophysical parameters and the reflectance captured by remote sensors.

The purpose of this study was to evaluate key biophysical parameters (biomass, canopy cover, and LAI) characterizing stands of *Spartina alterniflora* marshes in the Bahía Blanca Estuary, Argentina, and build models to relate these parameters to commonly used spectral indices derived from remotely sensed data. Through these models, we expect to test the suitability of remotely sensed vegetative indices for differentiating coastal marshes and assessing their ecological condition.

MATERIALS AND METHODS

Study Site

The Bahía Blanca Estuary is a mesotidal coastal system located in Argentina, along the Atlantic coast of South America, between 38°45′ S and 39°25′ S and between 61°45′ W and 62°25′ W (Figure 1). This system extends over 2500 km^2 (Melo, 2004) and is dissected by a series of major channels running from the NW to the SE. The mean tidal amplitude ranges from 2.2 to 3.5 m, and the spring tidal amplitude ranges from 3 to 4 m (Piccolo and Perillo, 1990). Two small rivers discharging less than 3 m^3 s^{-1} enter the estuary from the northern shore and represent the main sources of freshwater to the system (Carbone *et al*., 2008; Perillo *et al*., 1987). Freshwater inflow from other sources is restricted to periods of high local rainfall (Melo *et al*., 2003). Being in the northern limit of the Patagonian desert, seasonally hypersaline conditions commonly develop because of the high evaporation rates (Freije *et al*., 2008), and the coastal zone extends through salt flats where the low soil water potential eliminates all but the most tolerant halophytes (Pratolongo *et al*., 2009). Plant associations in the study area have been previously described by Verettoni (1961). *Spartina alterniflora* marshes are the only vegetation type appearing in the intertidal fringe, below the level of the mean high tide. These marshes commonly form discontinuous patches near the mouth of the estuary (Botté *et al*., 2008; Isacch *et al*., 2006; Peláez, Mazzon, and Pratolongo, 2009; Perillo and Iribarne, 2003).

Sampling and Data Collection

In order to analyze and quantify the influence of several biophysical parameters on the spectral behavior of *S. alterniflora* marshes at the Bahia Blanca Estuary, we measured the spectral response (in reflectance units) for 23 different stands of *S. alterniflora* located on several islands, as well as along the coastal fringe. We included in the analysis different types of marshes, in terms of elevation, soil characteristics, and plant height. Sampling areas were chosen in order to represent the range of environmental variation along the estuary. Surveys were performed in February 2009. Reflectance data were acquired using an ASD FieldSpec® (Analytical Spectral Devices, Boulder, Colorado) visible, near-infrared, and shortwave-infrared handheld radiometer (400-2400 spectral range, 25° Instantaneous Field of View [IFOV]). The radiometer was handled 80 cm above the soil surface in order to determine a 37-cm-diameter circle on the soil. A 50-cm-diameter circle containing the 37 cm one was used as the sample unit, in order to cover a buffer zone of influence of the surrounding vegetation. Measurements were performed under natural conditions and varying standing biomass by means of partial, random, successive harvesting of tillers, according to a procedure specially designed for the present work. For each site, a series of measurements was performed, the first corresponding to the natural condition before harvesting (T1), followed by a variable number of measurements performed after successive partial harvestings, and ending the series with a measurement on bare soil (Figure 2). The number of measurements constituting a series (four to six) was adjusted to the initial biomass present in the site. This method was designed in order to keep a constant soil influence for the different biomass scenes.

Since *S. alterniflora* grows in the intertidal zone, spectral measurements were taken at low tide to avoid water influence on the signal. Fieldwork was performed between 1000 and 1600 local time (3 h before and after nadir sun's position) to diminish shadow influence.

For this study, we considered the effects of standing biomass, LAI, and percentage canopy cover (PCC) on the spectral response. Standing biomass was determined as the vegetation

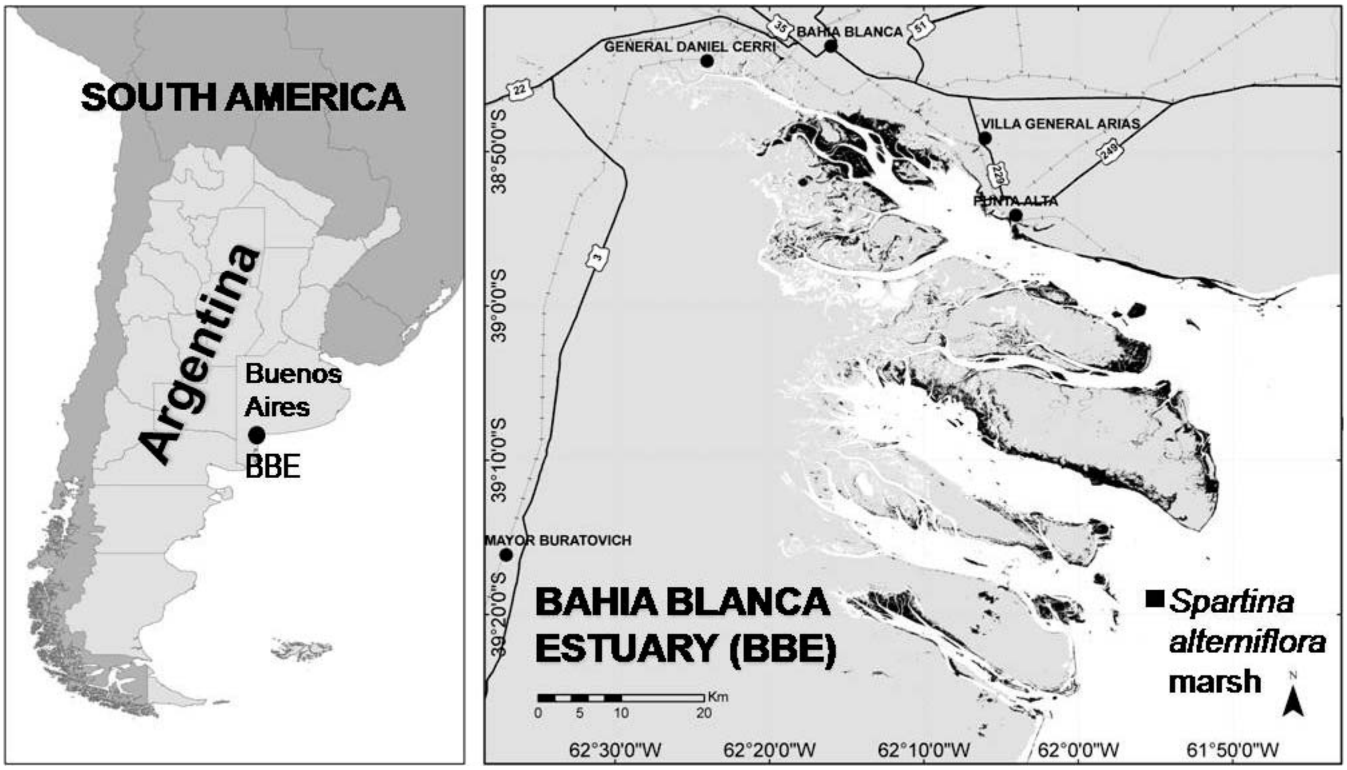

Figure 1. Location of Bahia Blanca Estuary (BBE) and *Spartina alterniflora* marshes in the study site.

weight after being dried at 70°C for 48 h. LAI was estimated as the sum of each individual leaf area, which was obtained by approximating the leaf to a triangle shape (measuring length and width), since *S. alterniflora* leaves are nearly a gently tapering isosceles triangle (lanceolate). Canopy cover was estimated from pictures taken vertically for each scene using the CAN EYE percentage canopy cover program (https://www4.paca.inra.fr/can-eye/). These biophysical parameters

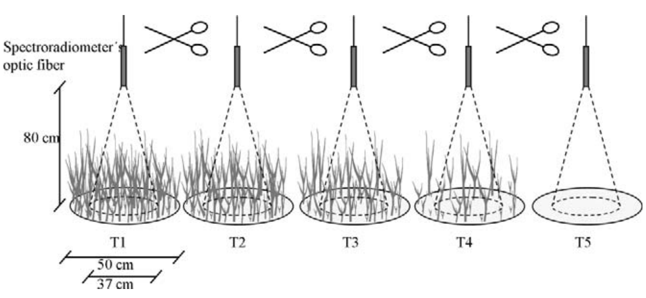

Figure 2. Sampling design with partial successive harvestings, specially developed for this work. The spectral reflectance of the same site at different times (T1 ... T5) was acquired. Between two consecutive times, plants were randomly harvested, diminishing canopy cover/biomass from an initial high biomass scene (T1) to a final zero biomass scene (bare soil, T5). Scissors represent random harvests.

were determined for each scene over the 50 cm circular sample units. In addition, average plant height and tiller density were determined for each site, at the different harvesting scenes. Superficial soil samples from the 23 *S. alterniflora* sites were analyzed for texture, water content, and organic matter.

Several synthetic indices were calculated (Table 1) and related to field observations. A set of vegetation and soil indices was calculated in order to determine the suitability of different sensors (*e.g.,* different bandwidths and central wavelengths) for estimating biomass, cover, and LAI. To select the indices that better explain these variables, a canonical correspondence analysis (CCA) was performed, followed by regression analysis on the selected indices.

Spectral Indices

The normalized difference vegetation index (NDVI) and SR (simple ratio) are structural indices (Eitel *et al.*, 2008), MCARI (modified chlorophyll absorption reflectance index) is a chlorophyll index (Daughtry *et al.*, 2000), and MSAVI (modified soil-adjusted vegetation index) and OSAVI (optimized soil-adjusted vegetation index) are indices designed to minimize the soil noise (Qi *et al.*, 1994). The NDVI is based on the contrast between the maximum absorption in the red band due to chlorophyll pigments and the maximum reflection in the infrared caused by leaf cellular structure. The photosynthetically active radiation absorbed by vegetation (APAR; Asrar,

Table 1. *Indices calculated in this study.*

Index	Index Equation	Author
$NDVI_{Rouse}$	(ρ864 - ρ671)/(ρ864 + ρ671)	Kriegler *et al.* (1969), Rouse *et al.* (1974)
$NDVI_{NOAA}$	(Avρ720-1100 - Avρ580–680)/(Avρ720-1100 + Avρ580–680)	
$NDVI_{Landsat}$	(Av ρ760–900 - Avρ630–690)/(Avρ760–900 + Avρ630–690)	
$NDVI_{Modis}$	(Av ρ841–876 - Avρ620–670)/(Avρ841–876 + Avρ620–670)	
$GNDVI_1$	(ρ800 - ρ550)/(ρ800 + ρ550)	Gitelson, Kaufman, and Merzylak (1996)
$GNDVI_2$	(ρ780 - ρ550)/(ρ780 + ρ550)	Gitelson, Kaufman, and Merzylak (1996)
$GRDI_{range}$	(Av ρ545–565 - Avρ660–680)/(Avρ545–565 + Avρ660–680)	
IRI	ρ740/ρ730	Reusch (1997)
$VARI_{green}$	(Avρ545–565 - Avρ660–680)/(Avρ545–565 + Avρ660–680 - Avρ470–490)	Gitelson *et al.* (2002)
PRI 1	(ρ529 - ρ569)/(ρ529 + ρ569)	Gamon, Peñuelas, and Field (1992)
PRI 2	(ρ570 - ρ531)/(ρ570 + ρ531)	Gamon, Peñuelas, and Field (1992)
WBI	ρ900/ρ970	
MCARI	(ρ700 - ρ670) - 0.2 (ρ700 - ρ550) (ρ700/ρ670)	Daughtry *et al.* (2000)
TCARI	3 [(ρ700 - ρ670) - 0.2 (ρ700 - ρ550) (ρ700/ρ670)]	Haboudane *et al.* (2002)
MSAVI	$0.5 \{2\,\rho800 + 1 - \sqrt{[(2\,\rho800 + 1)^2 - 8(\rho800 - \rho670)]}\}$	Qi *et al.* (1994)
ρ695/ρ420	ρ695/ρ420	Carter (1994)
ρ695/ρ760	ρ695/ρ760	Carter, Cibula, and Miller (1996)
ρ800/ρ550	ρ800/ρ550	Buschman and Nagel (1993)
REIP	700 + 40 [(ρ670 + ρ780)/2 - ρ700]/(ρ740 - ρ700)	Guyot and Baret (1988)
OSAVI	(1 + 0.16) (ρ800 - ρ670)/(ρ800)	Rondeaux, Steven, and Baret (1996)
SR	ρ800/ρ670	Jordan (1969), Rouse *et al.* (1974)

R = reflectance in the corresponding wavelength; ρ = reflectance; Av = average mean value for the wavelenght interval indicated; $NDVI_{Rouse}$ = normalized difference vegetation index as ascribed by Rouse *et al.* (1974); $NDVI_{NOAA}$, $NDVI_{Landsat}$, $NDVI_{Modis}$ = normalized difference vegetation index calculated for NOAA, Landsat, and Modis data; GNDVI = green NDVI; $GRDI_{range}$ = green red difference index; IRI = infrared index; $VARI_{green}$ = visible atmospherically resistant index; PRI = photochemical reflectance index; WBI = water band index; MCARI = modified chlorophyll absorption in reflectance index; TCARI = transformed CAR index; MSAVI = modified soil-adjusted vegetation index; REIP = red edge inflection point; OSAVI = optimized soil-adjusted vegetation index; SR = simple ratio.

Kanemasu, and Yoshida, 1985), has a direct and almost linear relation with NDVI, especially when the leaves are horizontal and the soil is dark (Sellers, 1989). The total biomass and green biomass are also closely related to the NDVI (Kennedy, 1989; Tucker, 1979). Percent green cover and also LAI have a positive association with the NDVI, especially when vegetation does not completely cover the ground (Kennedy, 1989; Kerr, Lagouarde, and Imbernon, 1992). Simple ratio vegetation indices directly compare signals between the reflection and absorption peak of chlorophyll pigments, which means they are sensitive to changes in chlorophyll content (Slater and Jackson, 1982).

Chlorophyll indices have been successfully used to retrieve plant chlorophyll concentration and LAI (Filella and Peñuelas, 1994; Gitelson and Merzlyak, 1996; Pinar and Curran, 1996). Leaf chlorophyll indices are also sensitive to variations in leaf cover and biomass (Eitel *et al.*, 2008). MCARI is based on the chlorophyll absorption ratio index (CARI; Kim *et al.*, 1994), which measures the depth of chlorophyll absorption at 670 nm relative to the green reflectance peak at 550 nm and the reflectance at 700 nm. CARI was designed to reduce the variability of the photosynthetically active radiation due to the presence of diverse nonphotosynthetic materials. It uses bands corresponding to the minimum absorption of the photosynthetic pigments, centered at 550 nm and 700 nm, in conjunction with the chlorophyll *a* maximum absorption band, around 670 nm.

Indices designed to reduce soil noise (MSAVI and OSAVI) derive from the first soil-adjusted vegetation index (SAVI; Huete, 1988; Huete, Justice, and Liu, 1994). The main shortcoming of SAVI is that a soil-brightness correction factor (L) has to be specified, creating a circular logic problem of needing to know the vegetation amount/cover before SAVI can be applied, the results of which are supposed to give information on the amount of vegetation/cover. This leads to the use of the default L value of 0.5. Qi *et al.* (1994) developed the modified soil-adjusted vegetation index (MSAVI) to more reliably and simply calculate L based on the slope of the soil line from a plot of red versus near-infrared brightness values. The MSAVI seeks to address some of the limitations of NDVI when applied to areas with a high degree of exposed soil surface (Jiang *et al.*, 2007). The optimized soil-adjusted vegetation index (OSAVI; Rondeaux, Steven, and Baret, 1996) was developed by using bidirectional reflectance in the near-infrared and red bands; in its formulation, a constant soil-adjustment coefficient (0.16) was selected as the optimal value to minimize variation with soil background. Its chief advantage is its simplified formulation and the lack of a requirement for *a priori* knowledge of the soil type. In any case, these indices reduce soil noise at the cost of decreasing the dynamic range of the index, and they are slightly less sensitive to changes in vegetation cover than NDVI at low levels of vegetation cover.

MAIN RESULTS AND DISCUSSION

Spectral profiles for *S. alterniflora* stands match with the characteristic spectral profile for vegetation (Jakubauskas *et al.*, 2000; Tucker and Sellers, 1986), showing low reflectance in the visible region of the spectra and increasing in the infrared region up to 0.3–0.4 (Figure 3). Vegetation absorbs most of the light in the visible part of the spectrum but is strongly reflective at wavelengths greater than 700 nm. This sharp change in

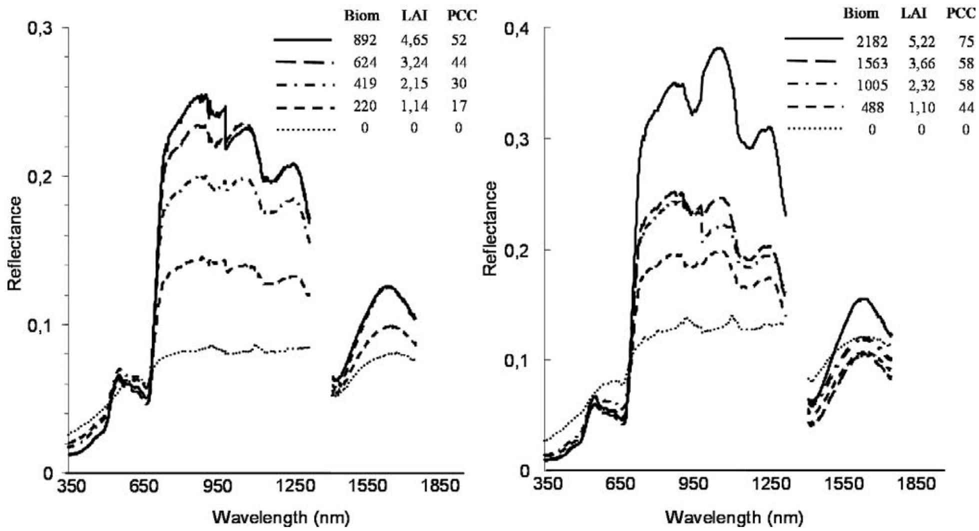

Figure 3. Spectral signatures for different biomass, PCC, and LAI levels in 2 of the 23 sites. Inside each graph, different plots indicate different biomass levels for the same site obtained by successive harvesting.

reflectance in the near-infrared range is commonly referred as the "red edge" (Horler, Dockray, and Barber, 1983; Horler *et al*., 1983), with variations that typically range from 0.05 to 0.5 reflectance between 680 nm to 750 nm (Artigas and Yang, 2006; Filella and Peñuelas, 1994; Pinar and Curran, 1996). At each individual site, the general pattern observed agreed with this theoretical trend, with lower absorption in the red wavelengths and lower reflectance in the near-infrared band as biomass decreased from T1 to T5 (Figure 3).

Results from the CCA showed that biomass, LAI, and PCC strongly and positively correlate each other (r = 0.838). According to several authors, LAI is closely related to biomass (Casanova, Epema, and Goudrian, 1998, Song *et al*., 2005; Sun *et al*., 2009; Zhao, Wang, and Nolte, 2008) and is also closely related to exposed area of living leaves and thus is a measure of the area exposed to capture incident electromagnetic energy. By being strongly correlated, any of these parameters can be accurately estimated from the others.

A negative strong correlation was found between the CCA first axis and the biophysical parameters (r = –0.920 for LAI and –0.985 for PCC). The vegetation indices with highest scores for the CCA first axis, and in consequence the indices that better explain variations in the biophysical parameters of interest, were: MCARI, MSAVI, SR, OSAVI, $NDVI_{landsat}$, $NDVI_{modis}$, $NDVI_{rouse}$ in that order.

In our work, the MCARI, MSAVI, SR, OSAVI, and NDVI indices showed strong correlations with the biophysical parameters LAI, biomass, and PCC (Table 2). These vegetation indices also had strong significant ($p < 0.05$) regressions with LAI, PCC, and biomass, with MCARI, MSAVI, and SR showing linear adjustments, whereas NDVI showed logarithmic ones and OSAVI showed logarithmic regressions for biomass and LAI and a linear regression for PCC (Table 3). Silva *et al*. (2008) pointed out that plant biomass can be estimated by means of spectral data, mainly through the use of regression analysis, with bands or band combinations as predictor variables, but the authors also found that the relationship between the spectral signal and the biophysical parameter commonly approaches an asymptote (Peñuelas *et al*., 1993). That is the case of the logarithmic regressions found in this work (NDVI and OSAVI for biomass and LAI; Table 3). According to the literature, NDVI saturates for a dense and multilayered canopy and shows a nonlinear relationship with biophysical parameters such as LAI (Baret, Clevers, and Steven, 1995; Baret and Guyot, 1991; Gilabert, Gandia, and Melia, 1996; Gitelson, Kaufman, and Merzlyak, 1996; Lillesaeter, 1982; Sellers, 1987; Vina *et al*., 2004).

MCARI, MSAVI, and SR had significant linear regressions showing no saturation at high levels of vegetation cover. Our results agree with those obtained by Haboudane *et al*. (2004), who found that the main difference between NDVI and MSAVI resides in the saturation effect as LAI increases: While NDVI reaches a saturation level asymptotically when LAI exceeds 2, MSAVI shows a better trend without a clear saturation at high

Table 2. *Coefficients of determination for correlations between biomass, PCC (percentage canopy cover), and LAI (leaf area index) and several vegetation indices derived from hyperspectral data. All correlations were significant at* $\alpha = 0.05$. N = *68*.

Index	Biomass	PCC	LAI
MCARI	0.79	0.86	0.86
MSAVI	0.82	0.92	0.85
SR	0.82	0.91	0.85
OSAVI	0.78	0.92	0.83
$NVDI_{Landsat}$	0.72	0.89	0.77
$NVDI_{Modis}$	0.72	0.90	0.77
$NVDI_{Rouse}$	0.72	0.89	0.76

Table 3. *Regression equations between biomass, PCC (percent canopy cover), and LAI (leaf area index) and several vegetation indices derived from hyperspectral data. All regression were significant at $\alpha = 0.05$.* N = *68.*

Index	Biomass	PCC	LAI
MCARI			
y	$3 \times 10^{-05}x + 0.0126$	$0.0009x + 0.0006$	$0.0132x + 0.0085$
R^2	0.63	0.75	0.74
MSAVI			
y	$0.0002x + 0.088$	$0.0059x + 0.0077$	$0.0796x + 0.0669$
R^2	0.67	0.84	0.72
SR			
y	$0.0028x + 1.7405$	$0.0802x + 0.6361$	$1.1041x + 1.4615$
R^2	0.68	0.83	0.72
OSAVI			
y	$0.1131\mathrm{Ln}(x) - 0.3438$	$0.0079x + 0.0669$	$0.1435\mathrm{Ln}(x) + 0.2923$
R^2	0.67	0.84	0.71
$\mathrm{NVDI}_{\mathrm{Landsat}}$			
y	$0.1429\mathrm{Ln}(x) - 0.3844$	$0.23\mathrm{Ln}(x) - 0.3135$	$0.1796\mathrm{Ln}(x) + 0.4194$
R^2	0.65	0.81	0.68
$\mathrm{NVDI}_{\mathrm{Modis}}$			
y	$0.1393\mathrm{Ln}(x) - 0.3535$	$0.2271\mathrm{Ln}(x) - 0.2933$	$0.1756\mathrm{Ln}(x) + 0.4298$
R^2	0.65	0.82	0.67
$\mathrm{NVDI}_{\mathrm{Rouse}}$			
y	$0.1462\mathrm{Ln}(x) - 0.3717$	$0.2347\mathrm{Ln}(x) - 0.298$	$0.1841\mathrm{Ln}(x) + 0.4502$
R^2	0.65	0.80	0.68

LAI levels (up to 6). According to Broge and Leblanc (2000), this explains, in part, why MSAVI has proven to be a better indicator of greenness measure. Based on radiative transfer models, MSAVI would also be a better LAI estimator in terms of sensitivity to canopy effects (Broge and Leblanc, 2000), being less affected by variations in canopy parameters as well as soil spectral properties in dense canopies (Haboudane *et al*., 2004). Based on these results, MSAVI is the most suitable index to retrieve LAI, offering a clear improvement over NDVI. This is an interesting result, considering that the majority of the papers that use remote sensing data use NDVI without checking the precision of their estimations.

CONCLUSION

The different levels of biomass, LAI, and PCC considered through this work were highly correlated to vegetation indices MCARI, MSAVI, and SR derived from field radiometry data, showing that the biophysical parameters of interest can be accurately estimated from remotely sensed reflectance. The main outcome of this work is a series regression equations built on local data, which set the basis for future applications involving the mapping of biophysical parameters in the study area, at a landscape scale, from satellite imagery. The regression equations, even limited to local applications, set a precedent for similar works worldwide. Given that *Spartina alterniflora* marshes are found across the world, either as a native or invasive plant, obtaining this type of regression model for marshes elsewhere, under different environmental conditions, would provide a valuable tool for monitoring and management of the species.

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