Int J Appl Earth Obs Geoinformation 68 (2018) 189–201

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

journal homepage: www.elsevier.com/locate/jag

Assessing biomass of diverse coastal marsh ecosystems using statistical and machine learning models

Yu Mo[a,*], Michael S. Kearney[a], J.C. Alexis Riter[a], Feng Zhao[b], David R. Tilley[a]

[a] Department of Environmental Science and Technology, University of Maryland, College Park, MD 20742, USA
[b] Department of Geography, University of Maryland, College Park, MD 20742, USA

ARTICLE INFO

Keyword:
Coastal marshes
Multispectral
Hyperspectral
Ground-based
Airborne
Spaceborne
Louisiana

ABSTRACT

The importance and vulnerability of coastal marshes necessitate effective ways to closely monitor them. Optical remote sensing is a powerful tool for this task, yet its application to diverse coastal marsh ecosystems consisting of different marsh types is limited. This study samples spectral and biophysical data from freshwater, intermediate, brackish, and saline marshes in Louisiana, and develops statistical and machine learning models to assess the marshes' biomass with combined ground, airborne, and spaceborne remote sensing data. It is found that linear models derived from NDVI and EVI are most favorable for assessing Leaf Area Index (LAI) using multispectral data (R^2 = 0.7 and 0.67, respectively), and the random forest models are most useful in retrieving LAI and Aboveground Green Biomass (AGB) using hyperspectral data (R^2 = 0.91 and 0.84, respectively). It is also found that marsh type and plant species significantly impact the linear model development ($P < .05$ in both cases). Sensors with coarser spatial resolution yield lower LAI values because the fine water networks are not detected and mixed into the vegetation pixels. The Landsat OLI-derived map shows the LAI of coastal mashes in Louisiana mostly ranges from 0 to 5.0, and is highest for freshwater marshes and for marshes in the Atchafalaya Bay delta. The CASI-derived maps show that LAI of saline marshes at Bay Batiste typically ranges from 0.9 to 1.5, and the AGB is mostly less than 900 g/m^2. This study provides solutions for assessing the biomass of Louisiana's coastal marshes using various optical remote sensing techniques, and highlights the impacts of the marshes' species composition on the model development and the sensors' spatial resolution on biomass mapping, thereby providing useful tools for monitoring the biomass of coastal marshes in Louisiana and diverse coastal marsh ecosystems elsewhere.

1. Introduction

Coastal marsh ecosystems offer valuable functions such as storm and flood protection, fishery resources, water purification, wildlife conservation, and carbon sequestration; yet they are increasingly under threat from natural and anthropogenic stresses including sea-level rise, hurricanes, and pollution (Morris et al., 2002; Howes et al., 2010; Deegan et al., 2012). The importance and vulnerability of coastal marshes necessitate effective ways to closely monitor them. Optical remote sensing is a powerful tool for this task. Its application for assessing coastal marshes' biomass dates back to the 1980s (Table 1). The first studies were done on *Spartina alterniflora* in saline marshes in Delaware (Hardisky et al., 1983, Gross et al., 1987). Later studies extended the application to species in lower salinity ranges to other geographic areas inside or outside the United States (Gross et al., 1986, 1993; Zhang et al., 1997; Jensen et al., 1998, 2002; Kearney et al., 2009; Trilla et al., 2013; Byrd et al., 2014; Ghosh et al., 2016). Although existing studies have demonstrated the potential of using optical remote sensing in monitoring coastal marshes at a landscape scale, they concentrated on saline marshes and focused on sites covered by single species, mostly *S. alterniflora*. How optical remote sensing can be applied to diverse coastal marsh ecosystems composed of a wide range of salinity and various plant species is less clear.

Diverse coastal marshes ecosystems, such as the ones in Louisiana, encompass habitats spanning a wide range of salinity and plant species with various leaf characteristics and canopy structures. Coastal marshes in Louisiana are subdivided into freshwater, intermediate, brackish, and saline marshes based on vegetation associations that correspond closely with the environmental modifiers such as salinity, water level, and tidal inundation duration (Gosselink, 1984; Visser et al., 2012). Plant species richness decreases from freshwater to intermediate to brackish to saline marshes, while dominance increases (Gosselink, 1984). Freshwater marshes are characterized by tall broadleaf plants (2–4 m) such as *Typha* spp., while the brackish and saline marshes are dominated by

* Corresponding author at: Department of Environmental Science and Technology, 1426 Animal Sci./Ag. Engr. Bldg., College Park, MD 20742, USA.
E-mail addresses: moyu@umd.edu, moyu6688@gmail.com (Y. Mo).

https://doi.org/10.1016/j.jag.2017.12.003
Received 13 March 2017; Received in revised form 10 December 2017; Accepted 13 December 2017
0303-2434/

Table 1
Summary of literature using optical remote sensing to estimate coastal marsh biophysical parameters. Acronyms for **(1)** vegetation indices: normalized difference vegetation index, NDVI; infrared index, II; sample ratio, SR; soil adjusted vegetation index, SAVI; Global Environmental Monitoring Index, GEMI; atmospherically resistant vegetation index, ARVI; Soil and Atmospherically Resistant Vegetation Index, SARVI; modified chlorophyll absorption in reflectance index, MCARI; modified soil adjusted vegetation index, MSAVI; optimized soil-adjusted vegetation index, OSAVI; atmospheric and soil vegetation index, ASVI; green vegetation index, VIGreen; enhanced vegetation index, EVI; wide dynamic range vegetation index, WDRVI; chlorophyll index red, CIred; chlorophyll index green, CIgreen; infrared summation index, ISI; green normalized difference vegetation index, GNDVI; visible atmospherically resistant index, VARI; **(2)** biophysical variables: total aboveground biomass, TAB; live leaf biomass, LLB; live aboveground biomass LAB; total fresh mass, TFM; green fresh mass, GFM; aboveground green biomass, AGB; leaf area index, LAI; percent canopy cover, PCC; aboveground dead biomass, ADB; vegetation fraction, VF; leaf chlorophyll content, CHLl; and other **(3)** Partial least squares regression (PLS).

Methods	Biophysical Parameters	Best R^2	Location	Species	Reference
Landsat TM derived NDVI, II	TAB, LLB	0.9	Lewes, DE, US	*Spartina alterniflora*	Hardisky et al. (1983)
Landsat TM derived NDVI, II	TAB, LLB, LAB	0.89	Brittany, France	*Spartina anglica*	Gross et al. (1986)
Landsat TM derived NDVI	LAB,	0.7	Lewes, DE, US	*Spartina alterniflora*	Gross et al. (1987)
Landsat TM derived NDVI	LAB	0.89	Lewes, DE, US	*Typha angustifolia*	Gross et al. (1993)
Landsat TM derived SR, NDVI, SAVI, GEMI, ARVI, SARVI	TAB, TFM, GFM, AGB	0.72	San Pablo Bay, CA, US	Saline marshes	Zhang et al. (1997)
Airborne multispectral SR, NDVI, ISI, IRVIS, SAVI, ARVI, SARVI	TAB, LAI	0.77	Murrells Inlet, SC, US	*Spartina alterniflora*	Jensen et al. (1998)
Airborne multispectral SR, NDVI, SAVI	TAB, LAI	0.67	National Estuarine Research Reserve, SC, US	*Spartina alterniflora*	Jensen et al. (2002)
Landsat TM derived NDVI	LAI	0.96	Chesapeake Bay, MD, US	Brackish marshes	Kearney et al. (2009)
Narrowband MCARI, MSAVI, SR, OSAVI, NDVI	TAB, LAI	0.84	Bahia Blanca Estuary, Argentina	*Spartina alterniflora*	Trilla et al. (2013)
MODIS and Landsat derived broadband NDVI	PCC	0.82			
PLS using simulated Hyperion, Landsat 7, and World View-2	AGB	0.46	Sacramento–San Joaquin Delta, CA, US	Dominated by *Typha* spp.	Byrd et al. (2014)
PLS using image from Hyperion, Landsat 7, and World View-2	AGB	0.45			
Airborne broadband NDVI, SAVI, MSAVI, ARVI, ASVI, VIGreen with LiDAR	LAB, ADB, TAB	0.47	Galveston Island, TX, US	*Spartina alterniflora*	Kulawardhana et al. (2014)
MODIS derived broadband NDVI, EVI, WDRVI, CIred, CIgreen, SAVI, GNDVI, and VARI	LAI, VF, CHLl, AGB	0.68	Northern Gulf of Mexico, US	Saline marshes	Ghosh et al. (2016)
Landsat MSS, TM, ETM+, and OLI, ASTER, AVHRR, MODIS, SPOT, and SENTINEL-2 MSI derived SR, NDVI, ARVI, SAVI, SARVI, and EVI	LAI	0.7	LA, US	Freshwater, intermediate, brackish, and saline marshes	This study
Narrowband SR, NDVI, ARVI, SAVI, SARVI, and EVI	LAI, AGB	0.93, 0.71			
Airborne spectroscopy with random forest model	LAI, AGB	0.91, 0.84			

smaller plants that are around one-meter height or less such as *S. alterniflora* (Penfound and Hathaway, 1938).

This study examines the application of optical remote sensing on assessing biomass of the diverse coastal marsh ecosystems in Louisiana. We sample spectral and biophysical data from all freshwater, intermediate, brackish, and saline marshes, and develop statistical and machine learning models to map the biomass of the marshes with combined ground, airborne, and spaceborne data. The impacts of the species composition on the model development and the sensors' spatial resolution on biomass mapping are also investigated.

2. Methods

2.1. Ground sampling

2.1.1. Sampling sites

Forty-three sites in east Barataria Bay, LA, were sampled on 16–22 Aug 2015 (Fig. 1A; Table 2). The sites are in freshwater, intermediate, brackish, and saline marshes, corresponding to habitats with salinity of < 0.5 ppt (fresh), 0.5–5 ppt (oligohaline), 5–18 ppt (mesohaline), 18–30 ppt (polyhaline), respectively. The sites were selected because they were covered by dominant and common species in Louisiana's coastal marshes with wide ranges of canopy height and structure. Due to logistical reasons, more sites were from saline marshes compared to the other three marsh types, but the saline sites were covered by species also commonly found in the brackish, intermediate, and freshwater habitats, such as *Acnida cuspidate*, *Distichlis spicata*, *Iva frutenscens*, *Vigna luteola*, and *Spartina patens*. The sites were sampled for spectral and biophysical (i.e. leaf area index, LAI; aboveground biomass; and canopy height) data. In each site, vegetation spectral and LAI data were collected from four measurements, canopy height from three measurements, and aboveground biomass from two measurements (Fig. 1B). Average values were calculated for the multiple measurements within each site.

2.1.2. Biophysical measurements

LAI of the marshes was estimated using the GreenCropTracker software (Liu and Pattey, 2010) and downward photos taken by a camera (Canon PowerShot ELPH 110 HS, 6.16 × 4.62 mm sensor and 4 mm focal length) held at around 1.4 m height (equals to ground area about 1.5 × 2 m^2). This method derives LAI from the gap fraction of top-of-canopy digital color photography, which is strongly correlated (R^2 = 0.83) to actual LAI estimates. Briefly, this method assumes that the foliage is azimuthally uniform and spatially randomly distributed, and thus the relationship between canopy gap fraction and LAI follows the Poisson distribution. The canopy vertical gap fraction, hence, can be directly measured by quantifying the proportion of background pixels (including non-green leaf materials) of downward photos. Although this method is developed from upland crop ecosystems, it is also applicable to coastal marshes as its assumptions and calculations are not sensitive to water in the background substrates (Zhao et al., 2012).

Aboveground biomass was collected from circular plots of 0.5 m^2 (Site 1–16, 21, 22, and 25–43) or 0.26 m^2 (Site 17–20, 23, and 24). The different sizes of the plots are due to logistics reasons, but they did not impact the results because the biomass is calculated for per unit area. All aboveground biomass within the plots was gathered, put into labeled plastic bags, and then transported to the laboratory for further processing. Green (live) and brown (senescent or dead) biomass were separated. A representative subsample (around 30% by wet weight) of each sample was dried at 80 °C for 24–36 h until constant weight, weighed, and used to calculate the weight of the original sample. Aboveground green biomass (AGB), aboveground brown biomass, and