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Anu Swatantran

University of Maryland, aswatan@umd.edu

Ralph Dubayah

University of Maryland

Dar A. Roberts

University of California, Santa Barbara, dar@geog.ucsb.edu

Michelle Hofton

University of Maryland

J. Bryan Blair

Goddard Space Flight Center

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Mapping biomass and stress in the Sierra Nevada using lidar and hyperspectral data fusion

Anu Swatantran^{a,*}, Ralph Dubayah^a, Dar Roberts^b, Michelle Hofton^a, J. Bryan Blair^c

^a Department of Geography, University of Maryland, United States

^b Department of Geography, University of California, Santa Barbara, United States

^c Goddard Space Flight Center, NASA, Greenbelt, MD, United States

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ABSTRACT

In this paper, we explored fusion of structural metrics from the Laser Vegetation Imaging Sensor (LVIS) and spectral characteristics from the Airborne Visible Infrared Imaging Spectrometer (AVIRIS) for biomass estimation in the Sierra Nevada. In addition, we combined the two sensors to map species-specific biomass and stress at landscape scale. Multiple endmember spectral mixture analysis (MESMA) was used to classify vegetation from AVIRIS images and obtain sub-pixel fractions of green vegetation, non-photosynthetic vegetation, soil, and shade. LVIS metrics, AVIRIS spectral indices, and MESMA fractions were compared with field measures of biomass using linear and stepwise regressions at stand (1 ha) level. AVIRIS metrics such as water band indices and shade fractions showed strong correlation with LVIS canopy height ($r^2 = 0.69$, $RMSE = 5.2$ m) and explained around 60% variability in biomass. LVIS variables were found to be consistently good predictors of total and species specific biomass ($r^2 = 0.77$, $RMSE = 70.12$ Mg/ha). Prediction by LVIS after species stratification of field data reduced errors by 12% ($r^2 = 0.84$, $RMSE = 58.78$ Mg/ha) over using LVIS metrics alone. Species-specific biomass maps and associated errors created from fusion were different from those produced without fusion, particularly for hardwoods and pines, although mean biomass differences between the two techniques were not statistically significant. A combined analysis of spatial maps from LVIS and AVIRIS showed increased water and chlorophyll stress in several high biomass stands in the study area. This study provides further evidence that lidar is better suited for biomass estimation, per se, while the best use of hyperspectral data may be to refine biomass predictions through a priori species stratification, while also providing information on canopy state, such as stress. Together, the two sensors have many potential applications in carbon dynamics, ecological and habitat studies.

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1. Introduction

Improved estimates of forest aboveground biomass, hereafter “biomass” from remote sensing are critical for reducing uncertainties in the global carbon cycle (Hese et al., 2005; Rosenqvist et al., 2003) and are an important goal for future satellite missions. Although coarse-scale biomass estimates are well documented in temperate forests, they are mostly in the form of field measurements and averages over administrative units (Houghton, 2005). There is a need for higher resolution and spatially continuous estimates to quantify carbon flux and disturbance at scales at which land use activities occur (Houghton, 2005; Keith et al., 2009). Spatial distribution of carbon stocks in combination with species composition and vegetation stress can improve the understanding of ecosystem processes (Chambers et al., 2007; Ustin et al., 2004), carbon dynamics, and habitat structure (Bergen et al., 2007). The availability of such maps over difficult mountain terrain

such as the Sierra Nevada can be particularly valuable for natural resource and wildlife habitat management.

Many studies have demonstrated the efficacy of waveform lidar in accurately measuring three-dimensional vegetation characteristics including biomass for different forest cover and types (Drake et al., 2002a; Lefsky et al., 2002). Lidar metrics are less prone to saturation effects even at high biomass levels (Drake et al., 2002a; Hyde et al., 2007a; Lefsky et al., 2002) unlike most remote sensing indices, which saturate at moderate values (Gao, 1996; Huete et al., 1997). Acquiring wall-to-wall coverage of airborne lidar however, is expensive. A promising alternative is to extrapolate forest structure from lidar samples using continuous remotely sensed data. There is considerable interest in fusing sparse but accurate lidar measurements with optical (Asner et al., 2008; Hudak et al., 2002; Hyde et al., 2007a; Kimes et al., 2006) and radar sensors (Treuhaft et al., 2004) to improve prediction accuracy and spatio-temporal coverage of forest structure.

Imaging spectrometers or hyperspectral sensors provide many attributes complementary to canopy structure from lidar and can be used to discriminate vegetation types based on spectral characteristics (e.g. Clark et al., 2005; Dennison & Roberts, 2003; Martin et al.,

* Corresponding author.

E-mail addresses: aswatan@umd.edu, aswatantran@gmail.com (A. Swatantran).

1998). Studies have suggested that spectral attributes (Bergen et al., 2006; Ustin et al., 2004) and species composition (Anderson et al., 2005; Rosenqvist, et al., 2003) from hyperspectral data could improve biomass estimates in conjunction with lidar. However, it is still unclear as to how biophysical and biochemical attributes from hyperspectral data relate with structural attributes from lidar. There also remains considerable uncertainty on the efficacy of combining lidar with hyperspectral sensors for species-specific biomass mapping. Underlying causes of biomass change such as physiological stress, tree mortality and senescence cannot be detected from lidar alone, as it does not differentiate between healthy and stressed vegetation (Rosenqvist et al., 2003). While the ability of hyperspectral data to map stress is recognized (Asner, 1998; Merton, 1998; Roberts et al., 1997), the combined use of the two sensors for mapping vertical structure and stress remains largely unexplored.

Our goal in this study was to explore fusion of waveform lidar from the Laser Vegetation Imaging Sensor (LVIS) with hyperspectral imagery from the Airborne Visible Infrared Imaging Spectrometer (AVIRIS) for mapping biomass and stress in the diverse montane forests of the Sierra Nevada. In particular, we evaluated whether addition of spectral metrics from AVIRIS improved biomass estimates from LVIS. We also assessed whether species stratification using AVIRIS data prior to lidar estimation of biomass increased accuracy. Lastly, we explored the combined potential of the two sensors for mapping stress in the high biomass forests of the Sierra Nevada.

2. Background

Lidar and hyperspectral remote sensing are two potentially complementary technologies capable of providing comprehensive structural and biophysical characteristics of vegetation (Koetz et al., 2007). Lidar instruments record the time taken by laser pulses to reach the earth's surface from an aircraft/satellite and back to calculate distance to target. Discrete return lidar devices provide one or more laser returns that can be used for high resolution mapping of terrain and canopy elevation (Lefsky et al., 2002). Waveform lidar instruments digitize the entire outgoing and return signal to provide waveforms, from which various parameters such as subcanopy topography, canopy height, foliage profiles and vertical heterogeneity may be derived (Blair et al., 1999; Dubayah et al., 2000). Waveform metrics from small and large footprint lidar have been used to predict biomass in tropical (Clark et al., 2004; Drake et al., 2002b) and temperate forests (Anderson et al., 2005; Hyde et al., 2005; Lefsky et al., 2002).

Hyperspectral sensors measure vegetation absorption and scattering characteristics in the visible, near infrared and short wave infrared wavelengths of the electromagnetic spectrum. Spectral indices or band ratios from hyperspectral data provide many attributes useful for ecological studies (Ustin et al., 2004) such as chlorophyll content (Elvidge & Chen, 1995), canopy water status (Gao, 1996; Serrano et al., 2000), vegetation stress (Merton, 1998) and lignin and cellulose content (Curran et al., 2001; Kokaly & Clark, 1999). Narrow band and derivative-based indices from hyperspectral data are relatively less affected by background soil reflectance (Elvidge & Chen, 1995), illumination, saturation (Gao, 1996; Pu et al., 2003; Roberts et al., 2004), and other factors that influence broadband vegetation indices such as the normalized difference vegetation index (NDVI). Measures of liquid water (e.g. equivalent water thickness, EWT) from hyperspectral data are highly sensitive to canopy properties such leaf area index (LAI) (Roberts et al., 2004). Measures of plant dry matter have been related to environmental stress (Asner, 1998) and could improve lidar estimates of biomass in areas with low canopy heights and sparse vegetation cover (Bergen et al., 2006; Treuhaft et al., 2004; Ustin et al., 2004).

Spectral Mixture Analysis (SMA) is a widely used remote sensing technique for obtaining ecologically relevant and meaningful components from an image pixel (Adams et al., 1986; Chambers et al.,

2007). In SMA, two or more reference spectra/endmembers such as green vegetation, soil and shade are modeled as linear combinations to estimate sub-pixel fractions of each component. A limitation of SMA is that it uses only one set of reference endmembers to model all pixels in an image. Multiple endmember spectral mixture analysis (MESMA) (Roberts et al., 1998) allows the number and type of reference endmembers to vary on a per-pixel basis, accounting for spectral variability in the landscape and improving the accuracy of resulting fractions. Because MESMA fractions are calculated using the entire spectrum, they are more robust than traditional vegetation indices and have successfully been used for estimating live fuel moisture (Roberts et al., 2006), LAI (Sonnetag et al., 2007) and green biomass in pastures (Numata et al., 2008). MESMA has also been used to map vegetation (Dennison & Roberts, 2003) and urban land cover (Franke et al., 2009).

Most studies on lidar and hyperspectral fusion have focused on land cover classification. Asner et al. (2008) used lidar to mask gaps and low canopy heights, improving detection of invasive species from AVIRIS for Hawaiian rainforests. Koetz et al. (2007), classified fuel composition from fused lidar and hyperspectral bands using Support Vector Machines (SVM). Classification accuracies from fusion were higher than from either sensor alone. Mundt et al. (2006) fused co-registered lidar and hyperspectral data to map sagebrush communities and suggested further use of classified vegetation maps in biomass calculations. Few studies have explored the combined potential of the two sensors for biomass estimation. Anderson et al. (2008) used Minimum Noise Fraction (MNF) transformed AVIRIS bands in combination with LVIS and reported an 8–10% increase in biomass prediction accuracy for northeastern temperate forests. There is a need to test similar approaches over a wider range of forest cover and types, while retaining the physical significance of variables.

3. Study area and data

3.1. Study area

The study site (37°2'34.47"N, 119°9'33.81"W) covers an area of around 22,000 ha and lies along the western slopes of the Sierra National Forest (Fig. 1), in California, USA. The region has a Mediterranean climate with elevations ranging from 1000 m to 2500 m. Forests are dense and complex in structure with average biomass values of around 200 Mg/ha, and as high as 1000 Mg/ha in Giant Sequoia (*Sequoiadendron giganteum*) stands. Dominant species include red fir (*Abies magnifica*), white fir (*Abies concolor*), ponderosa pine (*Pinus ponderosa*), and California black oak (*Quercus kellogi*) (Hunsaker et al., 2002).

3.2. Data

3.2.1. Field data

Field surveys were conducted in 2000 and 2001 (Hyde et al., 2005). A modified stratified random sampling scheme was used to measure structural parameters over 500 plots in the northern and southern Sierra Nevada. Field plots were laid out to provide a statistically representative measure of structural variability for the eight major Wildlife Habitat Relation (WHR) types: montane hardwood, montane hardwood conifer, red fir, white fir, sierran mixed conifer, pines, wet meadow, and barren (Hyde et al., 2005; Mayer & Laudenslayer, 1988). Structural variables for live trees such as height, diameter at breast height (DBH), crown form, canopy cover, species, heights of dead snags and snag decay classes were recorded for concentric plots with radii of 15 m (0.07 ha—footprint level) and 56.4 m (1 ha—stand level) respectively. For 1 ha plots, only large trees with dbh greater than 76 cm were measured. A detailed description of the methods used for field data acquisition is available in Pierce et al. (2002). The study area in the Sierra National forest had 285 measured

Fig. 1. Study area in the Sierra National Forest showing 1 ha field plots. Plots are classified based on Wildlife Habitat Relation (WHR) type (Table 1).

plots out of which 125 1 ha plots had collocated lidar, hyperspectral and field measurements and were used for analysis (Table 1). The 0.07 ha plots were not used in this study because of increased geolocation errors between reprocessed lidar and field data.

3.2.2. Lidar data

The Laser Vegetation Imaging Sensor (LVIS) is a medium footprint, waveform digitizing, scanning laser altimeter, designed, and developed at NASA's Goddard Space Flight Center. LVIS operates at altitudes up to 10 km with a 7° field of view and uses laser pulses with a wavelength of 1064 nm for profiling vertical vegetation structure (Blair et al., 1999). NASA flew LVIS over the Sierra National Forest in summer 1999 at an altitude of 7 km with trees in leaf-on condition. The lidar shots had a nominal footprint radius of 12.5 m. The data had a swath width of 1 km and covered an area of 175 km². The subset used for this study had around 892,444 lidar footprints. Footprints were contiguous along track and overlapping across track (see <http://lvis.gsfc.nasa.gov/>).

3.2.3. Hyperspectral data

The Airborne Visible Infrared Imaging Spectrometer (AVIRIS) designed and developed at the Jet Propulsion Laboratory, measures

upwelling radiance from the earth's surface in wavelengths between 350 nm and 2500 nm in 224 contiguous bands with a bandwidth of 10 nm (Green et al., 1998). Fine spatial resolution AVIRIS images were acquired over the Sierra Nevada in July 2003. Radiometrically corrected images were processed to retrieve apparent surface reflectance using the MODTRAN based forward inversion approach as described in Green et al. (1993) and Roberts et al. (1997). The images were geometrically corrected using Digital photo Ortho Quads (DOQQ). The AVIRIS data consisted of three overlapping scenes covering a total area of 22,000 ha. Each image had a nominal spatial resolution of 3.3 m with 224 spectral bands. Bands with a poor signal-to-noise ratio from atmospheric interference of water vapor and carbon dioxide were eliminated, resulting in 118 bands for analysis.

4. Methods

The data sets used in this study had different geographical projections and were brought into a common frame of reference using the Universal Transverse Mercator Projection (UTM 19N) and NAD 1983 datum. Spatial overlay of AVIRIS and LVIS data showed good geolocation for analysis at the 1 ha level and no further rectification was performed. All hyperspectral processing were done using VIPER tools ENVI-Add on Module[®] (Roberts et al., 2007) and a hyperspectral metrics add on module.

4.1. Field attributes

Species-specific allometric equations from the USDA Forest Service (Waddell & Hiserote, 2003) were used to calculate biomass for all trees with dbh greater than 76 cm within 1 ha plots. Tree height, species, and dbh measurements from field data were used as inputs for calculating biomass of bole, bark, branches, and foliage separately for each tree. Biomass values for individual trees were then added to obtain aboveground biomass per hectare for large trees within each field plot. Field plots were classified based on WHR type for analysis by species/vegetation type. Although WHR types consist of species associations,

Table 1
Distribution of field plots by Wildlife Habitat Relation (WHR) type.

Species/WHR type	Number of plots 1 ha (LVIS, AVIRIS, field)
WTM (wet meadow)	8
BAR (barren)	3
RFR (red fir)	32
WFR (white fir)	27
SMC (Sierran mixed conifer)	37
PPN/JPI (pines)	18
GSQ (Giant Sequoia)	1
MHC/MHW	11
Total	137

most of them have a dominant plant genus/species. The MHC/MHW plots consisted of mixed hardwoods and conifers with broadleaf oaks (*Quercus* sp.) as the dominant vegetation type. Plots classified as PPN were mostly composed of ponderosa pine (*P. ponderosa*). SMC plots had mixed conifers including pines (*Pinus* sp.), firs (*Abies* sp.), and incense cedar (*Libocedrus decurrens*) with shade tolerant white fir (*A. concolor*) becoming increasingly dominant after regeneration from fire (Zald et al., 2008). RFR plots were almost entirely composed of red fir (*A. magnifica*) trees.

4.2. LVIS metrics

An LVIS waveform essentially consists of a signal with amplitudes proportional to energy reflected from intercepted surfaces within canopy and ground. LVIS footprints are geo-located to the global reference ellipsoid WGS 84, using a combination of GPS and Inertial Navigation System (INS) information (Blair et al., 1999; Hofton & Blair, 2002). Ground elevation is determined by identifying the center of the lowest mode in the waveform greater than mean signal noise (Fig. 2). Canopy elevation is the height at which the signal increases beyond a certain threshold (usually 3σ) at the top of the waveform (Hofton & Blair, 2002). The difference between canopy elevation and ground elevation gives the canopy height metric or height of 100% laser energy return (RH100). The 1999 LVIS data were reprocessed using new algorithms for ground detection and an improved horizontal geolocation algorithm (Blair et al., 2006). For each LVIS waveform, quartile heights of laser energy return i.e. height of 25% (RH25), 50% (RH50) and 75% (RH75) energy return were calculated in addition to RH100 (Fig. 2). Canopy cover was calculated from the ground energy return of each waveform normalized by the canopy and background reflectivity ratio (Ni Meister et al., 2001). We used a ratio of 1.6, derived from a previous study (Hyde et al., 2005). LVIS metrics were calculated for lidar shots within 1 ha plots and summarized to obtain minimum, maximum, mean and standard deviation for all metrics.

4.3. AVIRIS spectral metrics

Reflectance spectra (e.g. Fig. 3) were extracted from AVIRIS images over field plots to construct a spectral library for the study area. A set of 19 hyperspectral indices (Table 2) was calculated to quantify vegetation attributes from each spectrum and aggregated to obtain mean and standard deviation of values for 1 ha plots. These mainly

Fig. 3. Examples of reflectance spectra extracted from AVIRIS images over the study area. A set of 19 band ratios describing vegetation characteristics such as chlorophyll content, water content, stress was calculated from the visible, near infrared and short wave infrared wavelengths.

included vegetation indices, derivatives of the chlorophyll red edge, water band ratios, and ligno-cellulose band ratios. Indices based on the green, red, and blue wavelengths were found to be more robust than NDVI in estimating vegetation fractions (Gitelson et al., 2002). We tested the use of green band vegetation indices (VARIGREEN and VIGREEN) in addition to NDVI, Enhanced Vegetation Index (EVI), and Ratio Vegetation Index (RVI) for biomass prediction. Water absorption features in the infrared regions of the spectrum (e.g. 980 nm 1450 nm, and 1940 nm) are sensitive to canopy biophysical properties (Roberts et al., 2004; Serrano et al., 2000). The Normalized Difference Water Index (NDWI), Equivalent Water Thickness (EWT), and Ratio Water Index (RWI) were used as measures of canopy water content. The red edge or the rapid change in chlorophyll reflectance in the visible and near infrared portion of the spectrum provides a measure of chlorophyll content (Elvidge & Chen, 1995) and vegetation stress (Merton, 1998). We used the first and second derivatives of the red edge as measures of

Fig. 2. Example of an LVIS waveform centered on a field plot with an area of 0.07 ha. The amplitude of the waveform is proportional to energy reflected from canopy and ground. Metrics calculated from the waveform include ground elevation, quartile heights of energy return (RH25, RH50, RH75 and RH100) and canopy cover.

Table 2

Hyperspectral metrics calculated using AVIRIS data for 1 ha field plots included vegetation indices, red edge derivatives, ligno-cellulose band ratios, and MESMA fractions of green vegetation, soil/NPV, and shade.

Variable	Hyperspectral metric (mean, std. deviation)	Reference
IDL_DGVI	First derivative of red edge normalized to 626–795 baseline	Elvidge and Chen (1995)
1DZ_DGVI	First derivative of red edge normalized to 626 baseline	Elvidge and Chen (1995)
2DZ_DGVI	Second derivative of red edge normalized to 626 baseline	Elvidge and Chen (1995)
EVI	Enhanced Vegetation Index	Huete et al. (1997)
EWT	Equivalent Water Thickness	Roberts et al.
LC2 BAND RATIOS	Area, asymmetry, depth, width, wavelength of SWIR ligno-cellulose absorption feature (range 2045–2218 nm)	Kokaly and Clark (1999)
NDVI	Normalized Difference Vegetation Index NDVI	Tucker (1979)
NDWI	Normalized Difference Water Band Index	Gao (1996)
RWI	Ratio Water Band Index	Peñuelas et al. (1993)
RVI	Ratio Vegetation Index	Jordan (1969)
RVSI	Red Edge Vegetation Stress Index	Merton (1998)
REDEGEWAVE	Red Edge Wavelength	Pu et al. (2003)
REDEGEWAVE	Magnitude of red edge	Pu et al. (2003)
VARI GREEN	Visible Atmospherically Resistant Vegetation Index Green	Gitelson et al. (2002)
VIGREEN	Vegetation Index Green	Gitelson et al. (2002)
SHADE FRACTION	Fraction of vegetation shade within each pixel (calculated using MESMA)	MESMA, Roberts et al. (1998)
GV FRACTION	Fraction of green vegetation within each pixel (calculated using MESMA)	MESMA, Roberts et al. (1998)
SOIL + NPV FRACTION	Fraction of soil + nonphotosynthetic vegetation within each pixel (calculated using MESMA)	MESMA, Roberts et al. (1998)

chlorophyll content. Wavelength, asymmetry and area of lignin and cellulose absorption features (2045 nm–2218 nm) (Curran et al., 2001; Kokaly & Clark, 1999) were used to identify non-photosynthetic vegetation; their usefulness in improving biomass estimates in combination with LVIS data was also tested.

4.4. MESMA fractions from AVIRIS

The reflectance of an image pixel over a forested area is typically composed of varying combinations of bare soil, shade/shadows, green vegetation (GV) from foliage and non-photosynthetic vegetation (NPV) from dead bark, leaf litter or senescent vegetation (Chambers et al., 2007; Roberts et al., 2004). Multiple endmember spectral mixture analysis (MESMA) involves creation of regionally specific libraries by using reference spectra from an image, field, or modeled spectra. Each spectrum in the reference spectral library is modeled as a combination of another spectrum and shade (Dennison et al., 2004).

Three fit metrics are used to identify representative spectra or endmembers for each class: Count Based endmember (COB) (Franke et al., 2009; Roberts et al., 2003), Endmember Average Root mean square error (EAR) and Minimum Average Spectral Angle (MASA). COB values are used to select endmembers that model spectra within the same class (In COB) better than those in other classes (Out COB). EAR values are used to select spectra with lowest root mean square error in modeling other spectra of the same class (Dennison & Roberts, 2003). Spectra with low average spectral angle values (MASA) are selected as reference endmembers. A detailed description of MESMA and fit metrics can be found in Dennison et al. (2004).

A library was created for the Sierra Nevada from AVIRIS images by extracting reference spectra for grass, shrubs, trees, soil, and NPV

using field data and image interpretation. Each spectrum in the library was modeled as a combination of another spectrum and shade. We selected endmembers with high In COB values followed by those with low MASA and EAR values (Table 3). Several models with varying combinations of endmembers were tested using SMA/MESMA. For this study, we used 10 three-endmember (soil, green vegetation, and shade) models for unmixing the AVIRIS images. Soil and NPV endmembers were combined into one class. The resulting image consisted of fractional abundances of green vegetation, soil/NPV, and shade for each pixel at 3.3 m nominal spatial resolution (Fig. 4). MESMA fractions were then summarized to calculate mean and standard deviation of values for 1 ha field plots.

4.5. Land-cover classification from AVIRIS

We also used MESMA to classify land cover and dominant vegetation type from AVIRIS images. A spectral library was constructed from the AVIRIS images using field knowledge, coarse vegetation type maps (USDA Forest Service CALVEG data, 2007), lidar height maps, and image interpretation. We isolated patches of vegetation with dense canopy cover and extracted relatively pure spectra for oaks (*Quercus* sp.), white fir (*A. concolor*), red fir (*A. magnifica*), mixed firs (*Abies* sp.), and pines (*Pinus* sp.). Field knowledge was used to avoid plots with abundant ground cover of chaparral (*Ceanothus* sp. and *Arctostaphylos* sp.) and reduce mixing with canopy dominant spectra. Spectral metrics from AVIRIS such as NDVI, NDWI, EWT, and lignocellulose band ratios were also useful for separating non-photosynthetic vegetation, bare soil, and spectra for dominant vegetation types.

Each spectrum in the library of 183 spectra was unmixed with another spectrum and shade resulting in 182 unique two endmember models for each spectrum. Fit metrics EAR, MASA, and COB (see Section 4.4) were used to select suitable reference endmembers for land cover classification. We selected 47 spectra from several classes including pines, hardwoods, grass, soil, NPV, and chaparral. All AVIRIS images were unmixed using 47 two-endmember MESMA models to map land cover/dominant vegetation type (Fig. 5a). Outputs included dominant land cover type in each pixel and the corresponding fractional abundance. Pixels mapped as soil, rock, NPV, chaparral, and grass in the AVIRIS vegetation map were excluded. A vector grid of 1 ha polygons was placed over the species map and class statistics were calculated for pixels with pines, firs (red and white), and hardwoods within each polygon. The dominant class in each polygon was recorded to create an aggregated 1 ha species map (Fig. 5b).

5. Analysis

5.1. Stand level

The final data for stand level (1 ha) analysis included field-measured biomass, LVIS metrics, spectral indices, and MESMA fractions from AVIRIS. Wet Meadow (WTM) and barren (BAR) plots were excluded and 125 other plots with collocated LVIS, AVIRIS, and field data were used. We tested several linear and multiple stepwise

Table 3

Reference endmembers used in 10 3-endmember MESMA models for unmixing AVIRIS images. Soil and non-photosynthetic vegetation (NPV) spectra were grouped into one class. Fit metrics—EAR, MASA, and COB values were used to select the best representative spectra to un-mix the entire image.

Endmember	Class	Brightness	EAR	MASA	In COB	Out Cob	CoBI
Rock/soil	Soil/NPV	421.53	0.13	0.66	10	0	0
Soil	Soil/NPV	345.05	0.04	0.095	0	0	0
NPV	Soil/NPV	254.47	0.04	0.13	0	0	0
NPV	Soil/NPV	260.65	0.04	0.133	6	2	0.08
NPV	Soil/NPV	203.46	0.08	0.24	17	1	0.46
Green vegetation	GV	188.92	0.09	0.39	0	0	0
Green vegetation	GV	210.73	0.09	0.41	0	0	0

Fig. 4. Subset of images showing endmember fractions generated using MESMA. Bright areas have high fractional abundance and dark areas have low abundance. GV, soil/NPV and shade fractions were summarized to calculate mean and std. deviation of values for 1 ha plots.

regression models to predict biomass before and after species stratification. Models for predicting total and species-specific biomass were tested using AVIRIS metrics alone, LVIS variables alone and a combination of AVIRIS and LVIS metrics. Three parameters were used to select the best models; high co-efficient of determination values (r^2), low Root Mean Squared Error (RMSE), and p value <0.05 for r-squared as well as predictor variables. The Akaike information criteria (AIC) were used to select suitable predictor variables for all models. We also tested variable selection using Bayesian model averaging

(BMA). Confidence intervals for coefficients of determination were calculated to compare the statistical significance of different models.

5.2. Landscape level

Equations from stand level analysis were used to generate landscape maps to study variations between biomass from LVIS alone and species-specific biomass from fusion. The vegetation map at 1 ha had four classes: hardwoods, pines, white fir/mixed conifers, red fir. White fir (A.

Fig. 5. MESMA was used to map land cover and dominant vegetation types from AVIRIS images. AVIRIS maps at a resolution of 3.3 m (a) were aggregated and dominant vegetation type at 1 ha was identified (b). Labels show WHR types from field plots. *Forests classified with white fir as dominant vegetation type at 1 ha also had a mixture of conifers and were grouped as the SMC type for biomass estimation.

concolor) and red fir (*A. magnifica*), were grouped into one class at lower elevations (<2000 m) because of mixing. At the hectare level, mixing of species/genera within each class was unavoidable, but our vegetation classes closely matched the WHR type classification from the USDA Forest Service map at a coarser resolution. For example, polygons grouped as hardwoods were similar in distribution to the MHC/MHW type; pines were similar to the PPN type. Polygons with white fir as the dominant species also had a mix of pines, red fir and some hardwoods. These polygons were grouped under the firs/mixed conifer type. Biomass was calculated for each dominant vegetation type using equations derived from lidar and field data (Table 5).

Spatial patterns of AVIRIS vegetation indices, water band indices and red edge derivatives were analyzed in combination with lidar heights, canopy cover, and biomass predicted from fusion. We used the NDWI as an indicator of water content (Gao, 1996; Serrano et al., 2000; Maki et al., 2004) and the normalized first derivative of red edge, D1GVI as an indicator of chlorophyll content (Merton, 1998; Smith, 2004). The species biomass map from fusion was combined with NDWI and D1GVI maps to detect 1 ha stands with biomass greater than 200 Mg/ha, canopy cover greater than 40%, NDWI less than 0.05 and D1GVI less than 0.1. Stands with biomass greater than 200 Mg/ha, canopy cover greater than 40%, NDWI greater than 0.05 and D1GVI greater than 0.1 were identified as areas with relatively low stress. To rule out effects of soil reflectance on water band indices (Gao, 1996) we further analyzed NPV fractions within canopies alone by masking other land cover types.

6. Results

6.1. Stand level

AVIRIS variables explained around 60% of the variability in biomass ($r^2 = 0.60$, RMSE = 92.13 Mg/ha) with water band indices being the

most important variables (Fig. 6a). LVIS height metrics were found to be consistently better predictors of total and species specific biomass. The best model for stand level prediction had an $r^2 = 0.77$, RMSE = 70.12 Mg/ha, with RH75 being the single best predictor (Fig. 6b). AVIRIS metrics showed marginal improvement in biomass prediction (but not statistically significant) when combined with LVIS metrics for 1 ha plots ($r^2 = 0.80$, RMSE = 64.18 Mg/ha) (Table 4, Fig. 6c). AVIRIS variables including water band ratios (RWI, NDWI, EWT) and shade fractions from MESMA showed strong correlation with LVIS heights ($r^2 = 0.69$, RMSE = 5.2 m). Mean and standard deviation of shade fractions alone explained more than 50% variability in all LVIS metrics (for example, $r^2 = 0.54$, RMSE = 6.25 m for RH100).

Species-specific biomass relationships were analyzed for 125 plots (excluding barren and meadow plots). Classification of field plots by vegetation type/species before biomass estimation from LVIS improved prediction accuracy ($r^2 = 0.84$, RMSE = 58.78 Mg/ha) (Fig. 6d). The maximum increase in predicted values was observed for MHC/MHW plots with hardwoods as dominant vegetation ($r^2 = 0.94$, RMSE = 12.7 Mg/ha). For other dominant vegetation types, there was little change or even a slight increase in RMSE with species stratification (Table 5). RH75 was again the single best predictor of biomass for almost all vegetation types. AVIRIS metrics showed strong correlation with biomass for pines and hardwoods (r^2 greater than 0.7). Relationship between AVIRIS metrics and field biomass decreased considerably (r^2 less than 0.45) in high biomass plots of red fir (*A. magnifica*) and mixed conifers.

6.1.1. Statistical significance of models

Confidence intervals for coefficients of determination were calculated for all the models used to predict biomass (Fig. 7). Prediction using lidar variables alone showed a statistically significant improvement over the model using AVIRIS variables alone. Addition

Fig. 6. Biomass predicted for 125 field plots at a 1 ha scale using various metrics: (a) AVIRIS; (b) LVIS; (c) LVIS and AVIRIS metrics; and (d) LVIS after species stratification of field data.

Table 4

The predictive power of AVIRIS metrics alone, LVIS metrics alone, LVIS + AVIRIS metrics and LVIS metrics after species stratification of field data was tested over 125 1 ha plots. Suitable predictor variables were selected using AIC criteria. The best model was obtained by predicting biomass with LVIS variables after stratifying field plots into WHR/species type.

Regression model	Predicted biomass 56.4 m (1 ha) n = 125	
	R ² (95% C.I.)	RMSE (Mg/ha)
Field biomass ~ AVIRIS (Biomass = 8865 sdNDWI – 1624.13 sdNDVI – 5421.92 sdEWT + 3658.35 mean NDWI – 1218.99 mean EWT – 28.90 mean RVI + 20166.10 sdRVS – 125305.76 mean Rededgemag)	0.60 (0.49–0.69)	92.13
Field biomass ~ LVIS metrics (Biomass = 60.58 mean RH75 – 698.24 mean CCover – 27.84 mean RH100 + 149.18)	0.77 (0.69–0.83)	70.12
Field biomass ~ LVIS + AVIRIS metrics (Biomass = 55.83 mean RH75 – 24.76 mean RH100 – 776.32 mean CCover – 526.10 mean 1DZ_DGVI + 820.65 mean NDWI – 5299.80 sdldc2dpth + 339.99)	0.80 (0.74–0.86)	64.18
Species specific biomass from field ~ LVIS (equations in Table 5)	0.84 (0.79–0.88)	58.78

of AVIRIS variables to LVIS did not show a significant improvement over LVIS metrics alone. Species stratification prior to lidar estimation of biomass reduced prediction errors from LVIS alone by 12%, but the reduction was again not statistically significant. However, confidence intervals for the model using species stratification were narrower than the other models.

6.2. Landscape level

6.2.1. Classified land cover map

An error matrix was generated to assess the accuracy of the AVIRIS image classification. 183 reference spectra were modeled using 47 spectra in the selected MESMA model. Classification results showed an overall accuracy of 87.7% for level 1 (genera/species) with a kappa value of 0.86 (Table 6). Errors were higher because of mixing between white fir (*A. concolor*) and red fir (*A. magnifica*) spectra. Level 2 classification (plant functional type/genera) had a higher accuracy of 93%. It was noted that around 14 spectra in the original library were left un-modeled. Visual comparisons showed that the dominant vegetation types in the AVIRIS maps were similar to WHR types in the USDA Forest Service map. At the hectare level, we generated an error matrix using WHR types from field polygons as reference (Table 7). Overall accuracy for this classification was 69.5%. Accuracy could be lower (45%) in areas with greater mixing between pines, firs, and hardwoods. Accuracy was also lower because the reference maps

were classified as discrete polygons and were at a coarser scale than the AVIRIS classified map.

6.2.2. Biomass

Biomass maps predicted from LVIS before and after species stratification showed large differences in spatial variability, mainly in forests with hardwoods and pines as dominant vegetation type (Fig. 8). Histograms of biomass distribution before and after species stratification showed increases in predicted values for both hardwoods and pines in low biomass ranges (<50 Mg/ha) and decreases in high ranges (>200 Mg/ha) (Fig. 9). High biomass firs and mixed conifer stands showed little variation in predicted values before and after species stratification. Histograms of biomass for hardwoods and pines derived using classified AVIRIS maps and from USDA Forest Service vegetation maps showed similar trends in low and high biomass ranges.

6.2.3. Stressed biomass

Combined analysis of AVIRIS and LVIS metrics revealed spatial patterns that could not be detected from either sensor alone (Fig. 10). For most of the study area, water band indices, red edge derivatives and vegetation indices had very low values over barren land, exposed rock surfaces, and higher values over dense forests and wet meadows. However, we found low values for water band indices and vegetation indices in some high biomass (>200 Mg/ha) forests, particularly in red fir

Table 5

Biomass was predicted using a single lidar equation before species stratification and a different equation for each species after stratification of field plots by WHR type.

WHR type	Biomass predicted using single lidar equation Total biomass (actual vs. predicted) r ² = 0.77, RMSE = 70.12 Mg/ha		Biomass predicted using a different equation for each species. Species specific biomass (actual vs. predicted) r ² = 0.84, RMSE = 58.78 Mg/ha	
	r ² (95% C.I.)	RMSE (Mg/ha)	r ² (95% C.I.)	RMSE (Mg/ha)
Montane Hardwood Conifer (MHC) n = 10	0.82 (0.41–0.96)	22.6	0.94 (0.77–0.99) Biomass = 6.03 mean RH75 – 29.60	12.7
Sierran Mixed Conifer (SMC) n = 37	0.77 (0.60–0.88)	60.35	0.78 (0.61–0.89) Biomass = 49.69 mean RH75 – 20.98 mean RH100 – 553.06 mean CCover + 77.21	59.73
Red Fir (RFR) n = 32	0.82 (0.67–0.91)	71.02	0.83 (0.68–0.91) Biomass = 81.57 mean RH75 – 40.7512 mean RH100 – 1009.77 mean CCover + 255.02	69.82
White Fir (WFR) n = 27	0.70 (0.45–0.85)	75.59	0.70 (0.45–0.85) Biomass = 70 mean RH75 – 31.55 mean RH100 – 669.16 mean CCover + 86.42	74.63
Pines (PPN) n = 18	0.75 (0.46–0.90)	28.22	0.75 (0.43–0.90) Biomass = 5.95 mean RH75 – 45.84	28.7

Fig. 8. Landscape maps of biomass were generated from LVIS before (a) and after species stratification of AVIRIS imagery (b), using equations in Tables 4 and 5. Forests dominated by pine and hardwood species (e.g. black rectangle) show more spatial variations in predicted biomass.

The overlap of confidence intervals of the coefficients of determination before and after species stratification suggests that overall predictive power for biomass was not significantly higher at the species level for our study area. Part of the reason for this could be the relatively small sample size used in this study. The dominance of high biomass mixed conifers and low abundance of deciduous species in the study area could have also affected the results. Yet another factor could be the relatively coarse spatial scale of 1 ha used in our study, one that is large enough to encompass various species and canopy configurations. These limitations aside, stratification seemed to perform better at lower biomass levels. Increased prediction accuracy, lower RMSE values, and narrow confidence intervals suggest a small improvement with species stratification (Fig. 7).

We tested both linear and non-linear variables for all regression models. Best-fit models were obtained with linear combinations of variables. Although there is an apparent non-linear trend in Fig. 6a and Fig. 6c, it is because of the poor predictive power of the models in low biomass plots (<50 Mg/ha). The RMSE values from the regression models should be interpreted in terms of model-to-model comparisons rather than an absolute measure of accuracy in a mapping perspective.

Spatial predictions of biomass from LVIS were quite different before and after species stratification by AVIRIS. Relative to species-level equations, a single lidar equation underestimated values in the lower ranges and overestimated it in the higher ranges of biomass, particularly for hardwoods and pines. Using a different lidar equation for hardwoods and pines reduced apparent errors in lower ranges of

biomass for both these vegetation types (Fig. 9b and d). The trend towards reduced error and improved prediction accuracy was clear (Fig. 7) even at stand level analysis for hardwoods but not for pines.

Fusion of lidar and hyperspectral sensors at species level and in areas with low biomass is an important remote sensing research requirement (Bergen et al., 2006; Rosenqvist et al., 2003; Treuhaft et al., 2004). Our study shows that species stratification could potentially improve predictions from sparse lidar samples, in low biomass regions better than fusion with spectral metrics. More work is needed to confirm these results over larger samples and homogenous stands. Improving classification accuracies for individual species by using field spectra may further refine spatial prediction of biomass from AVIRIS. Also the optimum level of classification (plant functional type, genera or species) and scale (1 ha or less) must be studied further.

Intuitively, we would expect species stratification to provide an improvement because the data used for biomass ground truth is routinely derived from forestry tables on a species-level, just as we did in our research here. However, there is the larger, and unanswered question, of whether lidar metrics are sensitive to species-level differences in canopy vertical structure, canopy gap spatial pattern, stem density and stem spatial pattern, among others, that should be predictive of biomass, and at what spatial scales. While species-specific predictions as applied in this study could improve estimates over other forested areas, the true impact of a priori stratification may never be known unless this problem is explored thoroughly.

We did not expect a significant change in species composition within the time lag between lidar and hyperspectral data acquisition. However, some uncertainty in spectral metrics related to changes in

Fig. 9. Histograms showing differences between biomass predicted before (a and c) and after (b and d) species stratification of AVIRIS imagery. Stratification for hardwoods and pines increased predicted values in low (<50 Mg/ha) ranges and decreased values in high ranges (>200 Mg/ha) of biomass.

structure and stress may have affected the outcome. Another limitation was that only large trees (>76 cm dbh) were measured in 1 ha plots. Footprint level plots (0.07 ha) included measurements of all trees above

10 cm dbh but were not included in this study because of increased geolocation errors between reprocessed LVIS data and 2000/2001 field plot centers. Better geolocation of field, lidar, and hyperspectral data

Fig. 10. Landscape maps of biomass, canopy cover, NDWI and D1GVI used for detecting water and chlorophyll stress in high biomass forests.

Fig. 11. Map showing high and low stresses in stands with high biomass (>200 Mg/ha). Height of bars represents biomass values.

may help, but this may also only increase correlation between metrics rather than improve biomass estimates.

Spatial maps of various AVIRIS metrics in combination with LVIS maps showed increased water stress in many high biomass red fir (*A. magnifica*) and mixed conifer stands. High values of NPV fractions within canopies in addition to low vegetation and water band indices, suggests increased stress and mortality in these areas. Moisture stress was high in open stands with more canopy gaps as well as in dense stands, consistent with findings from Smith et al. (2005). Our results are similar to recent studies linking water stress and increased tree mortality in the Sierra Nevada (Lutz et al., 2009; Van Mantgem et al., 2009).

Areas within the Teakettle Experimental Forest (North, 2002), where red fir was the dominant vegetation type also showed a large number of NPV spectra in the 2003 AVIRIS images. Subsequent field observations in 2008 showed abundant dead trees as well as evidence of logging in these areas. Further analysis is required to confirm whether stress maps from 2003 AVIRIS images showed early

Fig. 12. Spatial distribution of non-photosynthetic vegetation (NPV) fractions within canopies for one AVIRIS image (1 ha level). Stands with high biomass and stress (Fig. 11) also showed high NPV values.

indications of the tree mortality observed in 2008. Presumably, lidar/hyperspectral data could be used to map areas of high stress and mortality in response to climate change as suggested by Van Mantgem et al. (2009).

8. Conclusion

Species stratification may improve predictions from lidar, a result only suggested by our work, as overall predictive ability did not improve significantly; however, confidence intervals were narrowed and biomass showed very different spatial variability when mapped across the landscape. Extrapolating structure from lidar samples with stratified optical data can be a promising strategy for mapping low biomass forests from future space borne lidar sensors such as DESDynI. Such species-specific biomass maps have the potential to be exceptionally useful for carbon and ecosystem modeling.

AVIRIS indices and MESMA fractions provide quantitative measures of canopy condition and can be of considerable value in ecological applications, when combined with lidar. We demonstrated one such application here, by mapping stress in high biomass forests of Sierra Nevada. Stress maps can serve as early indicators of mortality, drought, and fire susceptibility in old growth forests and help improve forest management practices. Classified vegetation maps can be further used to study regeneration from fire or combined with small footprint lidar data to map individual tree biomass/mortality.

Lidar can provide measures of vertical structure such as canopy height, understory cover, and foliage diversity while species composition, stress, and decadence can be obtained from hyperspectral data. Fusion of the two sensors is therefore, powerful for biodiversity and habitat studies. Future research will focus on combining the two sensors for mapping potential habitats for rare and endangered bird species.

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