

SPECTRAL IDENTIFICATION OF NATIVE AND NON-NATIVE PLANT SPECIES

Susan L. Ustin, Maria João Santos
University of California Davis, Davis, CA, U.S.A.

Abstract

The patterns of species distributions determine the functioning of ecosystems across a wide range of temporal and spatial scales, from biogeochemical cycles and partitioning of the energy budget, to changes in biodiversity, habitat characteristics, and trophic structures. To predict functionality, it is important to know the composition of species and other habitat characteristics. Loss of native biodiversity combined with near ubiquitous species invasions, global impacts of human-altered ecosystems, and climate change have made this a critical environmental issue. With few exceptions, even high spatial resolution remote sensing imagery has not been sufficient to identify and map individual species. In the past decade, the development of environmental spectroscopy from field spectrometers and airborne imaging spectrometers, has had marked progress in developing methodologies to identify individual species, as evidenced by a growing literature of case studies. There is need to further develop understanding of species identification at more fundamental levels, especially development of new measurement methodologies and rules for detection and mapping. We explore issues related to species identification and scale using field and image spectroscopy examples of invasive species that represent several growth forms and environmental conditions.

Introduction

Invasive Alien Species (IAS) are one of the major drivers of ecosystem change, second only to climate change (Mack et al., 2007). The presence of IAS in an ecosystem can determine its functioning across a wide range of temporal and spatial scales by altering biogeochemical cycles (Mack et al., 2001; Yelenik et al., 2004) and partitioning of the energy budget (Prater and DeLucia, 2006; Prater et al., 2006; Feng et al., 2007), resulting in changes in biodiversity (Henderson et al., 2006), habitat characteristics (Crooks, 2002), and trophic structures (Levin et al., 2006; Kappes et al., 2007; Neira et al., 2007; Aizen et al. 2008;). The diversity of forms and functions of IAS, combined with their typically rapid dispersal dynamics, render ground observations ineffective at monitoring invasive species distribution or quantifying the cascading ecological and economical consequences of their activity. Therefore, except at the smallest scales, remote sensing is needed to detect and monitor IAS.

Environmental spectroscopy (field and imaging spectroscopy) provides two advantages for detecting and monitoring IAS. The spectral resolution available from today's imaging spectrometers is sufficient to identify many individual IAS species, assuming that they are distinct from their surroundings due to differences in growth form, stand structure, timing of phenological activity, or physiological characteristics. Additionally, because analytical methods can be based on principles of spectroscopy, it becomes possible to develop automated systematic assessments of IAS, potentially at large scales. These advantages are demonstrated by the increasing number of published scientific investigations and agency reports that use environmental spectroscopy to map and quantify the distributions of IAS. For example, the journal *Remote Sensing of Environment* cites 62 papers since 2000, with 1-2 per year at the beginning of the decade and 10-20 per year at the end.

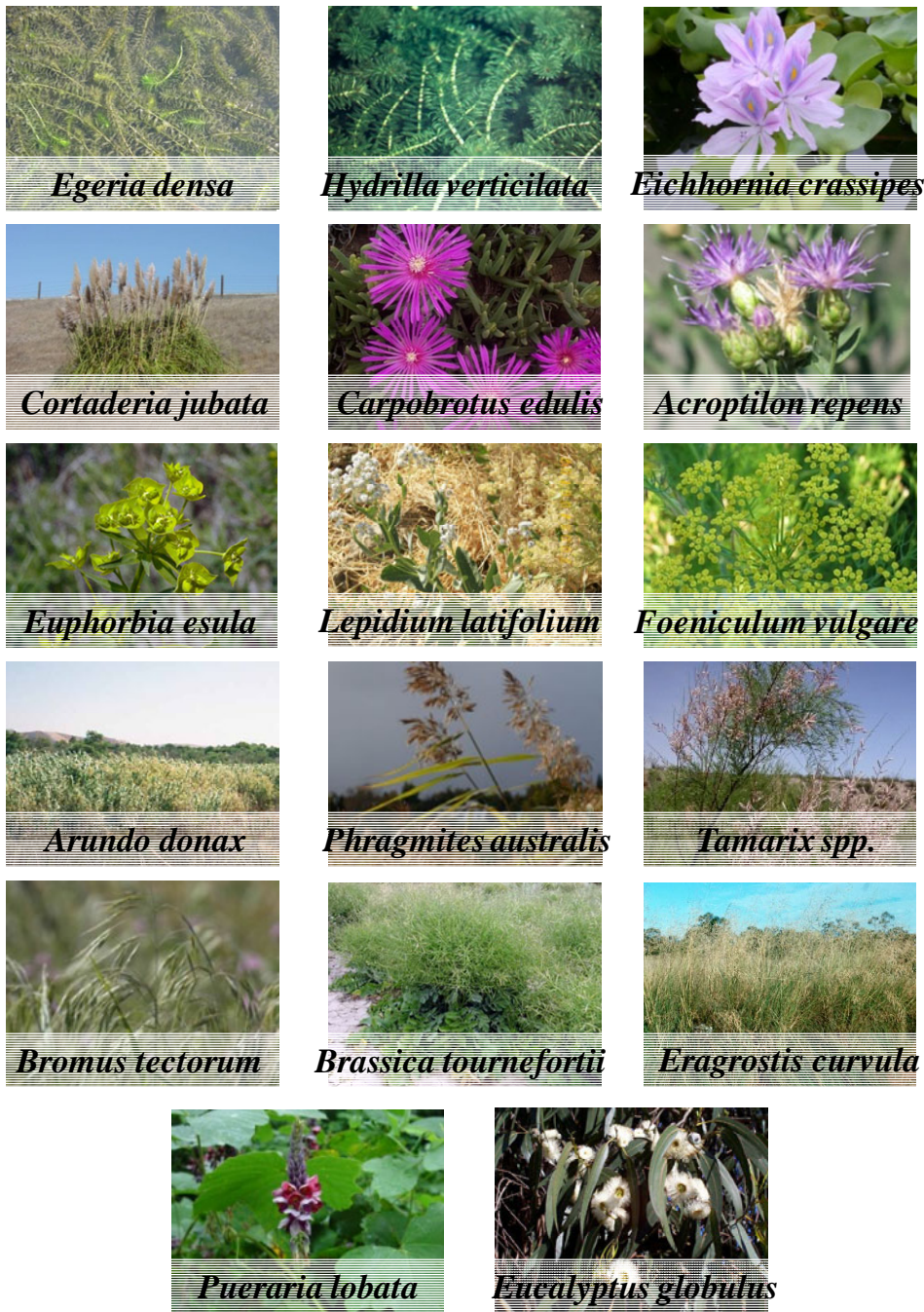


Figure 1. Scientific names and photos of IAS known to cause serious ecological problems to invaded ecosystems. These examples are IAS species that have been mapped using imaging spectroscopy and illustrate the range of growth forms and species characteristics. Locations where these species have been mapped using imaging spectroscopy and authors are provided in Table 1.

Yet, even with high resolution spectroscopy, mapping of individual species has been generally restricted to large monospecific vegetation patches, ecologically uniform conditions, homogeneous structure at the pixel resolution, or restricted to analysis of small datasets. Few studies have considered how species spectral identification changes with season, environmental conditions, and geographic locations. Even mapping large monotypic stands is challenging, unless the spectral properties of the

species stand out from co-occurring species. Conceptually, we have yet to resolve how to identify unique spectral signatures and develop spectral libraries for the estimated 400,000 extant plant species or how to group species in ecologically meaningful ways (e.g., functional types).

Table 1. Common and scientific names of target IAS, locations where they were successfully mapped, and authors.

Species name	Scientific name	Location	Reference
Brazilian waterweed	<i>Egeria densa</i>	Sacramento-San Joaquin River Delta, CA	Underwood et al., 2006b; Hestir et al., 2008; Santos et al., 2009, 2010
Water hyacinth	<i>Eichhornia crassipes</i>	Sacramento-San Joaquin River Delta, CA	Rajapakse et al., 2006; Khanna et al., 2010
Common reed	<i>Phragmites australis</i>	Aberdeen, MA	
Fennel	<i>Foeniculum vulgare</i>	Camp Pendleton, CA	
Giant reed	<i>Arundo donax</i>	Camp Pendleton, CA	DiPietro et al., 2002; DiPietro 2002
iceplant	<i>Carpobrotus edulis</i>	Vanderberg AFB, CA	Underwood et al., 2003, 2006a, 2007
Jubata grass	<i>Cortaderia jubata</i>	Vanderberg AFB, CA	Underwood et al., 2003, 2006a, 2007
Perennial pepperweed	<i>Lepidium latifolium</i>	Sacramento-San Joaquin River Delta, CA	Andrew and Ustin, 2006, 2008, 2009a,b; Hestir et al., 2008
Tamarisk	<i>Tamarix chinensis</i> , <i>T. aphylla</i>	Yuma Proving Ground, AZ	
Cheatgrass	<i>Bromus tectorum</i>	Yakima, WA	Noujdina and Ustin, 2008
Russian knapweed	<i>Acroptilon repens</i>	Yakima, WA	Noujdina and Ustin, 2008
Leafy spurge	<i>Euphorbia esula</i>	Theodore Roosevelt National Park, ND	O'Neill et al., 2000; Root et al., 2002
Weeping Lovegrass	<i>Eragrostis curvula</i>	Ft. Benning, GA	Cheng et al., 2007
Kudzu	<i>Pueraria lobata</i>	Ft. Benning, GA	Cheng et al., 2007
Tasmanian blue gum	<i>Eucalyptus globules</i>		Underwood et al., 2006a

The Center for Spatial Analysis and Remote Sensing (CSTARS) at UC Davis has used environmental spectroscopy to detect and map many IAS in the presence of native vegetation under a wide range of ecological conditions (Figure 1) across the continental United States. IAS have been successfully mapped using these techniques in a wide range of habitats including coastal zone, aquatic, riparian, semi-arid, shrub, grasslands, and deciduous forests and are representative of other studies in the literature today. Here we provide examples using environmental spectroscopy at field and image scales to map IAS and address issues related to identification and observation scales (Table 1). Many of these species have been mapped by others using imaging spectroscopy, including leafy spurge (Glen et al., 2005; Lawrence et al., 2006) spotted knapweed (Lawrence et al., 2006, and Tamarisk (Hamada et al., 2007).

Field Spectroscopy

At most sites, field spectral data were acquired under clear sky conditions, near solar noon (+/-2 hr), on or near the day of overflights using a FullSpec ProFR or a FieldSpec-3 (ASD, Inc., Boulder, CO). Measurement scales varied with IAS, however at typical field scales, with a 25° FOV held at nadir 1 m above the canopy (~ FOV of 0.2 m²). Data were calibrated to apparent reflectance using a leveled 10 cm x 10 cm Spectralon panel (Labsphere, Inc., North Sutton, MA) and measured at intervals of about 10-15 min. We acquired GPS data (GeoXT, Trimble, Inc., Sunnyvale, CA) to collocate the spectral data in the imagery. Measurements included invariant targets (e.g., roads, bare soil) used in secondary calibration of the images, canopy spectral measurements of target IAS and dominant plant species in the habitat, including different phenological stages (vegetative, flowering, fruiting, and senescent) where applicable. Additional targets included senescent vegetation, different soil types, etc. Data were processed and analyzed in Spectral Management and Analysis System (SAMS) (<http://www.cstars.ucdavis.edu/software-sams.htm>) and the Environment for Visualization of Images (ENVI, ITT, Boulder, CO).

Airborne imaging spectroscopy

Imaging spectroscopy data came from several sources including the Airborne Visible Infrared Imaging Spectrometer (AVIRIS) from the National Aeronautics and Space Administration (NASA; <http://aviris.jpl.nasa.gov>) and from commercial systems including HyMap (HyVista Corp., Sydney, Australia, <http://www.hyvista.com/>) and PROSPECTIR-V and PROSPECTIR-S (SpecTIR Inc., Reno NV, <http://www.spectir.com>). Spectral resolutions varied with wavelength and instrument, ranging from 6 to 17 nm and spatial resolutions of 3-12 m² pixels, providing sufficient spectral and spatial resolution to distinguish near homogeneous patches at the spatial scale of the target IAS.

Distinctiveness of IAS in the invaded ecosystem

Spectroscopy provides sufficient spectral detail to uniquely identify species, illustrated in these examples and confirmed by the growing body of literature in mapping IAS. In coastal dunes, the succulence of iceplant and its continuous prostrate growth form made its spectra distinct compared to the heterogeneous low cover xerophytic chaparral that it was invading (Underwood et al., 2003, 2006). Cheatgrass and Russian knapweed also had more continuous uniform cover and an herbaceous growth form that contrasted with the invaded sagebrush community (Noujdina and Ustin, 2008). Fennel was easier to map when invading the grassland habitat than the chaparral community because the timing of its phenology differs from the grasses. Nonetheless, the mixture tuned matched filter (MTMF) algorithm improved identification in the more heterogeneous and complex chaparral community. Jubata grass, a large bunchgrass, and the Tasmanian blue gum tree were distinct in canopy structure from the chaparral community, thus yielding good classifications for these species in chaparral (Underwood et al., 2006). Kudzu was successfully mapped in a deciduous forest using the spectral angle mapper (SAM) algorithm on the significant minimum noise fraction (MNF) bands (Cheng et al., 2007). Our overflights of desert IAS (2002) occurred during summer in the driest year on record for Arizona and in the middle of a major multi-year drought in the southwest U.S. (Breshears et al., 2005). Most plants were dead or

dormant and thus species differences were undetectable with the methods we used. All three target IAS of riparian ecosystems: giant reed, tamarisk, and common reed were successfully mapped where water was available for plants to be in an active stage of growth.

The ability of imaging spectrometers to capture spectral signatures of IAS is illustrated in the following examples of species of different life forms: submersed aquatic macrophytes, herbaceous perennials, riparian perennials (shrubs and cane-type grasses) and trees. These examples, shown in Figure 2 compare field measurements of IAS, using an ASD spectrometer, to airborne imaging spectroscopy data (HyMap and AVIRIS). In each panel, the general shape of the canopy spectra show the features expected of living green plants, with strong pigment absorptions in the visible spectrum, high near-infrared and lower shortwave-infrared reflectance. The terrestrial plants have two distinct water absorptions around 970 and 1200 nm. In general, the image data show the same spectral shape and magnitude as the field measured spectra, with the poorest agreement between field and image signatures in the aquatic species (upper panels, Figure 2). It is clear that the reflectance spectrum of each species is unique in this context.

Each of the IAS species in the panels on the right side of the figure is identified as being aggressive invasive species with high potential for environmental damage (CalIPC, 2006). The panels on the left are native species, with the exception of poison hemlock (*Conium macrophyllum*), which is a naturalized weed that is less invasive than the other examples (classified as “moderate” invader with uncertain ecological impacts by CalIPC), and here used for comparison because of its structural similarity to the highly invasive and ecologically damaging perennial pepperweed (*Lepidium latifolium*). The top row of panels (Figure 2), shows two submersed aquatic macrophytic species, coontail (*Ceratophyllum demersum*), a native species, and Brazilian waterweed (*Egeria densa*), an aggressive invasive species. In only 20 years Brazilian waterweed has become the dominant submersed species in the Sacramento-San Joaquin River delta, California. Submersed vegetation, including native and IAS is now present in about 10% of the more than 2000 km of delta waterways (Hestir et al., 2008). The canopy of Brazilian waterweed extends through the water column (up to depths of 7 m) and reduces water flow, thus affecting sedimentation rates and related hydrology and food and shelter resources for aquatic species. Its presence impacts recreational swimming, fishing and commercial/pleasure boating. The figure shows field-measured and HyMap image-measured reflectance of species based on field location data.

The next row of panels in Figure 2 is a pair of herbaceous perennial dicot IAS species, poison hemlock and perennial pepperweed, which range from 1 to 3m tall and invade saline to alkaline marshes, freshwater marshes, wet meadows, and grasslands. *Lepidium* spreads rapidly forming large monospecific stands that exclude native species, affecting food and nesting resources. The third set of panels show a pair of perennial riparian species, *Salix* ssp. (willow), a native woody shrub species common in riparian environments and the highly aggressive IAS *Arundo donax* (giant reed), a tall cane-like grass that grows in dense thickets up to 10m in height. Biomass accumulation in *Arundo* dominated areas increase wildfire risk, chokes stream channels increasing flood risk, changes riparian zone hydrology, blocks wildlife access to water and changes food resources (Plant Conservation Alliance’s Alien Plant Working Group, <http://www.nps.gov/plants/ALIEN/fact/ardo1.htm>). The last panel shows small trees/shrubs that are common to washes throughout the arid southwest. In this example we show *Cerceridium microphyllum* (palo verde or green stem), a small phreatophytic native tree/shrub that is drought deciduous and the highly invasive facultative phreatophyte salt cedar, most commonly *Tamarix parviflora* and *Tamarix ramosissima* but could include several *Tamarix* species. *Tamarix* species, although drought tolerant, are profligate water consumers, growing rapidly, accumulating high biomass, and increasing wildfire risk.

While the spectral shape of the field data are similar to the spectra extracted from the imagery, they are not identical, making it difficult to use these data in more than qualitative comparisons. The field spectra may have higher or lower reflectance than the image spectra, regardless of the number of spectra measured, which is largely a function of the spatial scale of the measurements and the canopy scale, as discussed later. This is well illustrated by the reflectance patterns in the aquatic species, which have significant spectral differences at the field scale but these differences are lost at the image scale where the two species are nearly spectrally inseparable. Because Brazilian waterweed is most often found in monospecific stands and is the most abundant species in the Delta, any identification of submersed vegetation is likely to be Brazilian waterweed. Coontail is far less frequently observed and it often co-occurs intertwined with Brazilian waterweed (Santos et al 2010), thus limiting our ability to identify it independently in the imagery.

The other general features these data show are that the absorption features (e.g., the water bands at 970 nm and 1200 nm) are generally stronger in the image than the field data which makes it possible to quantify some biochemical absorptions and use these physiological differences to aid species identification. This is a function of the leaf area density and light scattering in the canopy (Gao, 1996).

Issues of scale

A paper by Daughtry et al. (1982) illustrates how the spatial scaling and structure of the vegetation affects spectral measurements such that field data frequently do not match the image spectra of the same materials. Figure 3, adapted from Daughtry et al. (1982) shows that field data collected close to the canopy surface are highly heterogeneous. There is obvious variance between the above canopy and inter-row (between canopies) spectra. When data collected at a distance sufficient to allow the sampling area to extend across three rows and two inter-rows, the observation captures the average condition of the row-inter-row reflectance, and the spectral differences between rows and inter-rows is largely lost. Differences between field and image spectra (both wavelength specific and general magnitude) are primarily due to bias from under-sampling the full range of conditions or over/under sampling some conditions relative to their representative proportion, as well as view angle BRDF effects, including the three-dimensional structure of the canopy, also contribute. These differences in scaling are critical to a focus on mapping IAS, because identification of individual species requires measurements at scales relevant to the individual or patch. To detect all but the most extensive invaders, this scale tends to require small pixel sizes, at the submeter to a few meters in scale. Species mapping contrasts with more typical vegetation mapping, where a scale closer to the mean response for each land cover type is the desired size because the variability of individual species creates noise in the analysis.

Field versus airborne spectroscopy

The twenty year history of fast, portable, high spectral resolution field spectrometers has fundamentally changed remote sensing image analysis from using classical statistically based correlative methods to ones grounded in the physics of spectroscopy. Field instruments aid the detection and mapping of IAS through (1) analysis of preliminary spectral data used to identify the spectral signatures of target IAS within the imagery, and spectral features useful for their discrimination, (2) understanding the variability of IAS signatures and target image analysis methods, given phenological conditions, soil background reflectance, and the spectral characteristics of other species in the habitat, (3) improving the atmospheric and radiance calibration of imagery, and (4) providing capability to undertake experimental studies to understand canopy reflectance properties.

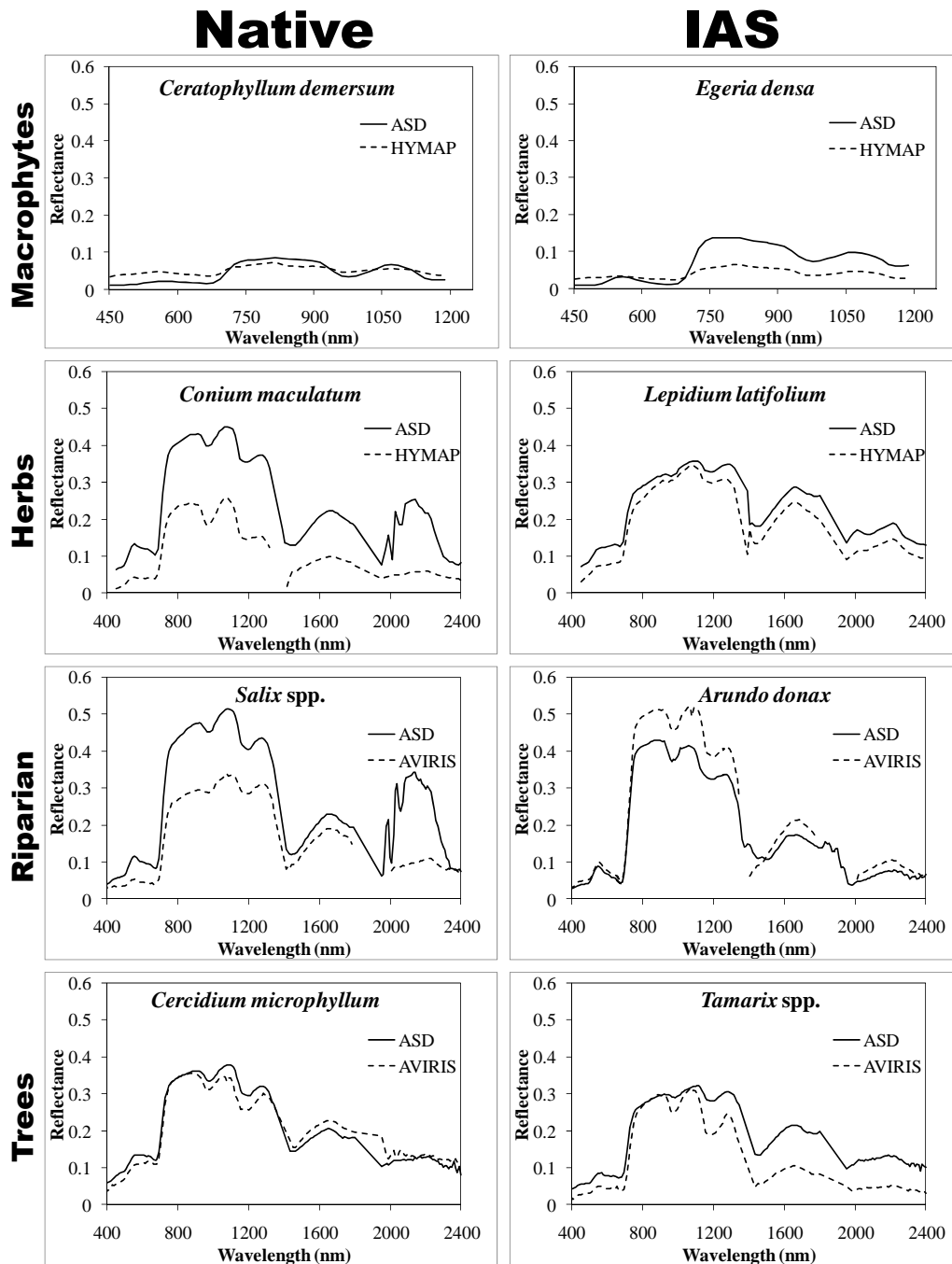


Figure 2. Comparison between field and image spectra for native and invasive plant species of different growth forms. The invasive species are identified on the “A” list of the most invasive plant pests by the California Invasive Plant Inventory (CalIPC, 2006). The CalIPC ranking identifies these IAS species as highly invasive, spreading rapidly, with widespread distributions and causing serious ecological damage.

Field data in IAS mapping

The use of field data in image analysis rarely extends beyond qualitative comparisons such as between spectra in spectral libraries and image spectra. One of the impediments to more quantitative comparison is that the statistical tools for analyzing field spectra (spreadsheets, statistical packages) are not the same as those used in standard image processing programs. We developed a tool, SAMS, to process field data using the same analytical methods used for image analysis, by importing field spectra as an image cube into ENVI/IDL. Figure 4 provides an illustration on how field spectra can be used to test the spectral separability of IAS from co-occurring species. The “Regions of Interest” (ROI) schematically shows the field spectra as pixels, with the colors indicating the name each spectrum was identified as when it was measured (black indicates no data). This shows the order that the field spectra were entered into the cube. In this example, the IAS leafy spurge (*Euphorbia esula*) spectra are schematically shown in the first line and part of the second. Snowberry (*Symphoricarpos albus*) and sweet clover (*Melilotus* spp.), the two most abundant native species, of 12 common associates (O’Neill and Ustin, 2000) are shown in the next several lines of pixels.

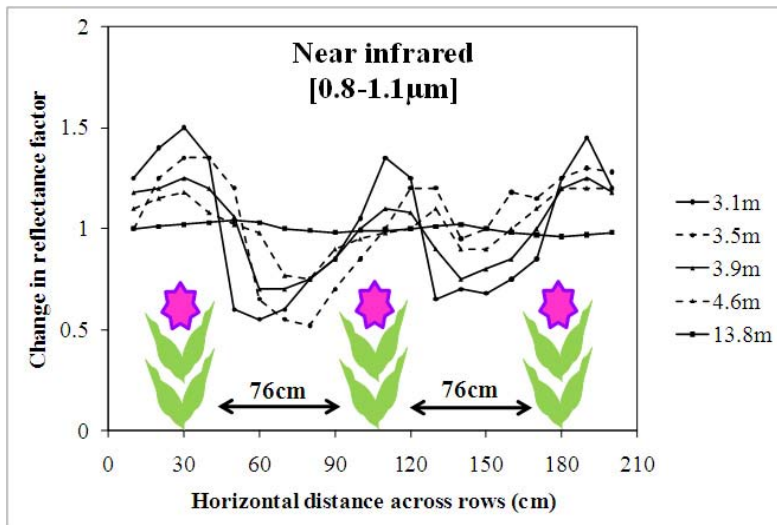


Figure 3. Spectral variability due to measurement distance and surface heterogeneity. Measurements were made at different heights above the ground, at 15 cm intervals for 2 (~5% visible, ~12.5% IR) m (figure modified from Daughtry et al., 1982). Measurements closer to the canopy (3.1 m) show strong spatial variability in reflectance (other bands show similar patterns). As height increases, spatial averaging increases. The 13.8 m height covered three canopy rows and two inter-row areas.

We calculated the average for each set of field spectra as the representative endmember spectrum for that species (shown in the spectral plot). We then performed a linear spectral mixture analysis (SMA) using these endmembers on the field spectra. We expected that if the species were separable using the field spectra, the result of the SMA analysis (top right cube) would match the species it was identified as from the field data (top left cube). Our results showed a good agreement between the field data and the LSU output. Leafy spurge was correctly classified in all but one of the spectra (ie pixel on the top right cube), where it resembled a mixture of snowberry and sweet clover. This shows that at the canopy scale leafy spurge is spectrally distinct from the most common species in the habitat. Some snowberry appear to be mixtures of all three species while all sweet clover appear to be mixtures but the relative low and high cover differences are retained. The

spectral distinctiveness of these species is further shown in the n-dimensional visualizer (ENVI, Inc.). Yet at the image scale these differences were less distinct, although the Spectral Angle Mapper (ENVI, Inc.) appeared to provide a reasonable identification of leafy spurge in some habitats but not others (O'Neill and Ustin, 2000; Root et al., 2000).

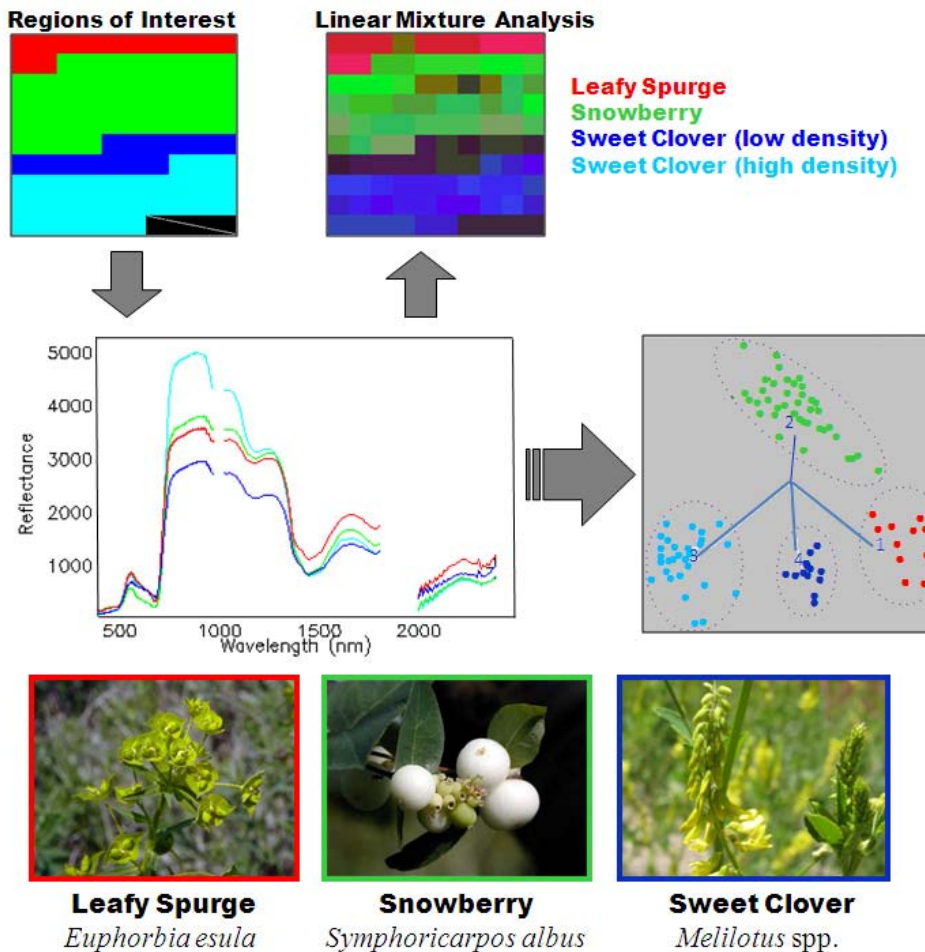


Figure 4. Use of field spectra to test spectral separability of IAS from common co-occurring native species. The pixels in the “Regions of Interest” cube represent field spectra that were identified as one of the three species or one density example. This is the *a priori* field identification of each spectrum.

Image calibration

Because of the generally small spectral differences between IAS and surrounding vegetation, accurate calibration is necessary to compare data over complex terrain or at multiple times. Figure 5 is an example of using field spectra of an invariant target (here asphalt) to verify the apparent reflectance derived from the calibration of the imaging spectrometer. This example, although from a 1999 dataset, is representative of observations today, even with the greatly improved spectral quality of the data. Clearly the similarity between the field and image spectra is evident but there are significant differences. The most obvious is that the image reflectance is lower than the field measurements across all wavelengths. This is due to insufficient field data and likely specular reflections and angular effects due to field measurement errors and the field-of-view (FOV) of the field spectrometer. Additionally there are wavelength effects, strongest at the edges of the water bands, and at the short and long wavelengths

ends of the spectra where signal-to-noise is poor and at the cross-over bands of the individual detectors. Additionally there is fine scale structure in these data due to measurement artifacts (e.g., AVIRIS reflectance adjacent to water bands, ASD noise between 900-100nm). While today's instruments have much better signal-to-noise and such artifacts are greatly reduced, identifying true spectral differences between IAS and the vegetation with which it is associated occurs at the magnitude of ~5% visible, ~12.5% IR reflectance differences. Thus continued improvement in both the instrument performance and in radiance and atmospheric calibration procedures is needed to better monitor detailed species composition of landscapes.

Comparison of ASD & Low Altitude AVIRIS Spectra in a Asphalt Calibration Site



Calibration Site

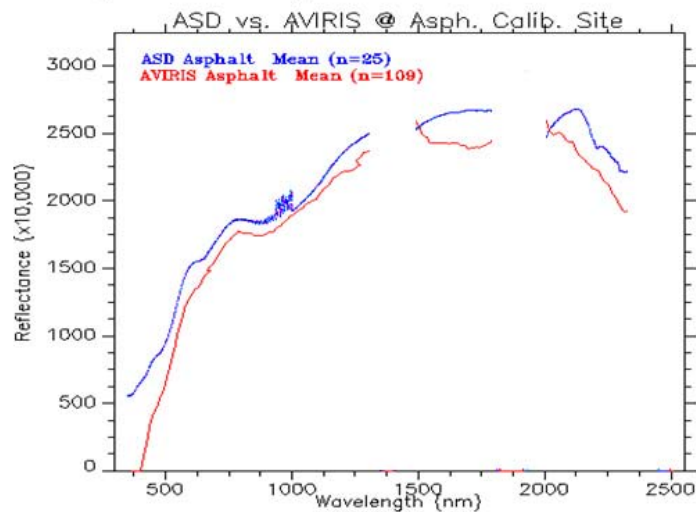


Figure 5. Accurate mapping of IAS requires good calibration of image data and knowledge of its performance. Mean ASD and AVIRIS spectra of an asphalt parking lot in Theodore Roosevelt National Park. The field spectrometer data are used to evaluate the calibration of the imaging spectrometer data to apparent reflectance.

Analytical tools

Image analysis software has significantly improved in the past two decades and commercial software is advancing rapidly. In our studies, different types of IAS and different ecosystem conditions have required different approaches to analysis to produce reliable maps of IAS distribution (Table 1). In all cases use of data from the full spectrum performed better than selecting just a few bands. This was true even when the target IAS had unique spectral features, e.g., the water absorption bands due to succulence of iceplant, compared to the water bands from the vegetation in the semiarid sclerophyllous chaparral community. For aquatic systems, knowledge-based binary decisions trees performed better than simple analytical methods that use one type of analysis, due to the low signal from the water combined with heterogeneous water quality (Hestir et al., 2008; Khanna et al., 2010). In terrestrial ecosystems, the best methods tended to follow the ENVI Hourglass method although decision tree and modeling approaches were also needed. In contrast with aquatic systems, success in terrestrial species mapping is primarily dependent on greater heterogeneity of growth forms and biochemistry. MNF transforms provided an excellent data dimensionality reduction and transformation on which to apply

other spectral matching methods such as Spectral Angle Mapper, Spectral Mixture Analysis, and Maximum Likelihood. IAS in riparian and semiarid systems required the use of MTMF to increase map accuracy (Table 1).

As ecosystems increase in species diversity and complexity, newer methods that systematically seek more sophisticated class-separating surfaces in the spectral space are needed. For example, modeling classes as Gaussian mixture distributions (McLachlan 1992), in a supervised or unsupervised classification framework, is obviously reasonable when the classes are known to be composed of several spectrally homogeneous sub-classes (Koltunov and Ben-Dor 2004). The appropriateness of multivariate normality assumption for each *sub-class* distribution has been frequently observed in experiments (e.g. Satnik and Vali 1983; Hjort and Mohn 1987; McLachlan 1992; Jimenez and Landgrebe 1998) and has received a strong theoretical support (e.g. Diaconis and Freedman 1984). However, classifiers based on more complex data models (statistical or not) require more training samples to provide stable results. This problem should be addressed by adopting improved data dimensionality reduction techniques for methods that fit many parameters, carefully designing sampling campaigns, as well as utilizing training samples whose class membership is not perfectly known. There are newer statistical and machine learning methods for dealing with uncertainty and assigning probabilities that have not yet been broadly accepted by the remote sensing community, but which could lead to better results, especially where less clear-cut boundaries exist between species or vegetation types.

Discussion

It is common place to use field spectroscopy as part of an image analysis program. A search in *Remote Sensing of Environment* for field and image spectroscopy of vegetation yields more than 500 papers. This review demonstrates the broad applicability of spectroscopy for IAS mapping although the number of publications is still low (order of 10s) but they demonstrate that these methods can be used to consistently and extend analysis of IAS beyond the initial datasets where they were developed and tested (e.g., see Hestir et al., 2008; Andrews and Ustin, 2008). Our field spectral studies support findings of Dennison and Roberts (2003) which show that field spectra can contribute to larger a mapping activity by providing information about spectral characteristics of individual species. One limitation of today's conceptualization of species characterization is the failure of researchers to produce a plant spectral library that can be used analogous to geologic libraries. Even if only dominant plant species are considered, the list is in the 1000s of plant species, and when phenological and stress states are added, the potential numbers of representative spectra is much higher. Nonetheless, when stratified by ecosystem type, the number of representative spectra that would need to be included becomes more reasonable, even if the phenological/physiological variability is still beyond current classification and database concepts. Roberts and colleagues have utilized the concept of regional spectral libraries (Roberts et al., 1998; Okin et al., 2001; Dennison and Roberts, 2003a,b) to develop databases for image analysis. Zomer et al. (2009) recently showed that field spectra observed for salt marsh species in mid-summer in California had the same spectral characteristics as the species from the Texas, Mississippi and Louisiana Gulf Coast, thus supporting an ecosystem focused database rather than a place-based one.

Figure 6 shows the scale limitation of current field-based and image-based measurement methods. Clumped low-stature vegetation that forms large isolated monospecific patches has great heterogeneity between patches at both field and imaging scales. For such cases, both field and image data can characterize the spectral properties of individual IAS species. Mixed patches of low-stature species can be identified in field data but species differences are lost at the image scale. For mixed life form

patches, including forest species or other tall vegetation, field observations are unable to capture the spectral characteristics of the trees, because it is unable to capture the structural information, but can continue to characterize low vegetation and spectral properties of soil and surface materials. Airborne spectrometry provides the only basis to measure the spectral properties of tree species that depend on their structural characteristics. However, image data do not detect sub-canopy species and soil characteristics.

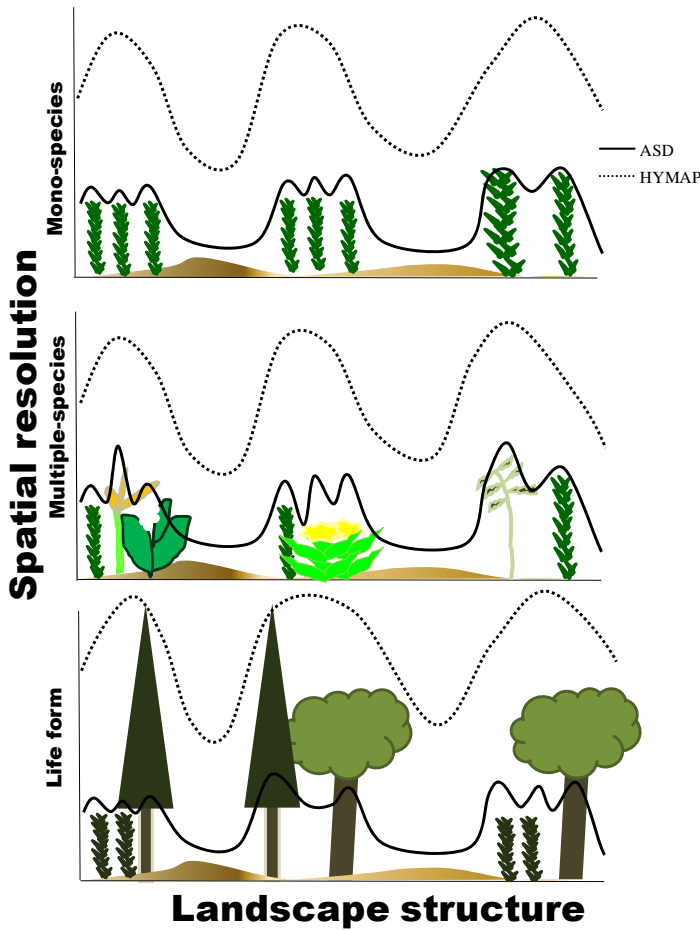


Figure 6. Illustration of scale constraints on field and airborne imagery for low-stature clumped monospecific stands, mixed species low-stature stands, and mixed life form stands. The solid lines illustrate the spectral reflectance in a band (such as shown in figure 3) that is measured at the ground scale by a field spectrometer and the dotted lines indicate reflectance measured by an airborne imaging spectrometer. Imaging spectroscopy cannot resolve mixed low-stature stands while field spectroscopy cannot measure above canopy measurements of forest vegetation.

Technical issues in IAS Detection

Spatial resolution

Spatial resolution requires some knowledge of the within class spatial (distributional) heterogeneity of the IAS and that of the background vegetation classes. For the sites we have studied, patches of IAS were routinely detected in imaging spectroscopy data at spatial resolutions of 9 to 12 m² (3 to 4 m pixels). Interestingly, Underwood et al. (2007) found better results when mapping the

heterogeneous composition of a chaparral community at the 30 m Landsat Thematic Mapper scale than at a 3 m pixel when the full spectral resolution of imaging spectroscopy was available. Such observations are consistent with geostatistical models like kriging that indicate when spatial resolution is too fine (e.g., within canopy crown measurements) measurement variability can overwhelm spatial correlation patterns that are found at somewhat coarser scales. Similarly, as shown above (Figure 4) if the pixel size is larger than the spatial resolution where correlations occur, then the data is not useful for IAS mapping. If the pixel scale is at the spatial resolution of the objects it can produce spatial aliasing and Moiré patterns. When spatial resolution is too coarse you again lose spatial correlation and inability to identify individual species. At this resolution it is necessary to emphasize spatial analysis with texture, object detection, etc. with spectral analysis. Under these conditions, it may be possible to better employ wavelets with spectral analysis to differentiate individual species. More research needs to be directed at determining the “right” spatial scale for spectroscopy measurements, particularly for IAS mapping. A geostatistical analysis of the spatial heterogeneity of the invasive species and the native plant background would provide the critical information needed *a priori* to determine the “best” spatial resolution. With more readily available high spatial resolution satellite data, e.g., GeoEye and Quickbird, perhaps some of the scale issues can be addressed using hyperspatial image data or even a creative use of Google Earth images.

Timing of image acquisition

The spectral information in the dataset is maximized when the greatest phenological differences are found between the IAS and the native species. Data collected in spring, when all species are simultaneously resuming active growth after winter and foliage is still immature, consistently yields the poorest results for identifying individual species. We found separation of IAS from background vegetation is best sometime after peak growth when species have accumulated more differences in their phenological states (e.g., Noujdina and Ustin, 2008). Differences can be further enhanced using multiple-date data, particularly combining data from different seasons. More research on timing of data acquisition is needed to determine if these patterns can be further generalized into a more theoretical sampling strategy. Field spectrometers could be deployed to make multi-temporal measurements through the growing season to resolve the “best” time to make airborne imaging measurements.

Technology limitations

Technological limitations are rapidly changing and imaging spectrometers are becoming more widely available, have significantly improved spectral resolution, expanded wavelength coverage (380nm to 12000nm), and higher optical fidelity than those used in this review. Repeated access to high quality data under a greater range of environmental conditions will advance understanding of detection issues.

Use of Field Data

Field spectral data provide information for calibrating and testing imagery reflectance, determining the spectral features of target species, and evaluating their detectability in the presence of other plant species. New methods are needed to improve the extent of spatial sampling and to obtain above canopy measurements of trees and other tall vegetation. There is also a need for new platforms that can make measurements a few meters above the surface.

The Future of Image Spectroscopy

Despite significant advances in instrument technology in the past 20 years, there has been little practical or theoretical development about how to obtain the large numbers of spectral samples that would meet statistical criteria for representativeness, given the typically large variability of the spectrally active materials in the environment. The limiting practical problem is not how to obtain a random or stratified sampling, or to select an appropriate sample size, but how to adequately sample the variability within tight time constraints. Field measurements normally should be made near solar noon (+/- 1 or 2 hrs) to match the time of overflight and reduce bidirectional reflectance distribution function (BRDF) effects. Because of specular reflectance at midday in aquatic systems, measurement must be made at lower sun angles. Measurements should be on the day of overflight, although most practically, they are limited to periods within a few days of overflights (assuming the weather doesn't change within the time period and assuming the goal is species mapping, not measuring biophysical processes).

Today's field spectrometers make rapid measurements, although the set-up (leveling the calibration panel, controlling for height, and pointing of the foreoptics) takes several minutes, limiting observations to about four per hour. The biggest time cost is the travel time between measurement locations. These temporal constraints result in insufficient data to adequately sample the full range of environmental conditions. More thought and development needs to be invested into how to (1) choose the most critical spectral samples to collect, (2) use the imagery itself to stratify the data and identify critical locations for sampling (this would require near real-time turn around) and (3) identify new types of platforms for measurement that will allow better spatial sampling. There has been some development of measurement platforms that can overcome some of these limitations. For example, the Center for Advanced Land Management Information Technologies (CALMIT) at the University of Nebraska-Lincoln has developed an "All terrain terrestrial vehicle data collection platform" termed "Goliath" that was designed primarily for crop research. It has ground clearance of 1.8 m. and a wheel base adjusted to row spacing. On this platform, spectrometers can be mounted on a 8.5 m extendable boom that can be raised an additional 12-15 m.

It may be possible to design robotic vehicles that would be suitable for making field measurements under at least some rough terrain and vegetation conditions of natural environments. An alternative direction is to develop miniaturized spectrometers that can be flown on small robotic planes, or on rotorcraft which can be programmed to fly GPS defined routes. This intermediate scale of "above canopy" observation capability has not been explored, except in few cases using remote controlled unpiloted airplanes (UAVs), e.g., Delacourt et al. (2009), Rango et al. (2009), and Zarco-Tejada et al. (2009). Rotorcraft, particularly the quadrotor type, has advantages for platform stability and control, particularly for "perch and stare" observations and catastrophic landings seem less likely than more traditional aircraft.

Wireless transmission of the spectrometer data has made it easier to make field measurements as has the reduced weight and size of these instruments. The current generation of field spectrometers too often fail under real field conditions, like summer midday temperatures in the western states which often exceeds 40° C, the high humidity of the southeast, and the extreme cold of winter measurements. Dust is also a problem. The equipment remains too heavy and awkward to easily carry under typical field conditions. The large laptops should be replaced by miniaturized PDA-sized devices that take advantage of other communication technologies, like iPhones, with internet capability, integrated GPS services, etc. Computer screens are notoriously difficult to see in sunlight and this presents another area where instruments could be improved for actual field use.

Lastly, the remote sensing community needs to invest in developing new analytical procedures and algorithms based on advanced models that represent the real-world complexity of the IAS mapping problem and account for the always too limited training data.

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