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BIODIVERSITY REVIEW

Benefits of hyperspectral remote sensing for tracking plant invasions

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ABSTRACT

Aim We aim to report what hyperspectral remote sensing can offer for invasion ecologists and review recent progress made in plant invasion research using hyperspectral remote sensing.

Location United States.

Methods We review the utility of hyperspectral remote sensing for detecting, mapping and predicting the spatial spread of invasive species. We cover a range of topics including the trade-off between spatial and spectral resolutions and classification accuracy, the benefits of using time series to incorporate phenology in mapping species distribution, the potential of biochemical and physiological properties in hyperspectral spectral reflectance for tracking ecosystem changes caused by invasions, and the capacity of hyperspectral data as a valuable input for quantitative models developed for assessing the future spread of invasive species.

Results Hyperspectral remote sensing holds great promise for invasion research. Spectral information provided by hyperspectral sensors can detect invaders at the species level across a range of community and ecosystem types. Furthermore, hyperspectral data can be used to assess habitat suitability and model the future spread of invasive species, thus providing timely information for invasion risk analysis.

Main conclusions Our review suggests that hyperspectral remote sensing can effectively provide a baseline of invasive species distributions for future monitoring and control efforts. Furthermore, information on the spatial distribution of invasive species can help land managers to make long-term constructive conservation plans for protecting and maintaining natural ecosystems.

Keywords
Biochemical and physiological properties, phenological change, plant invasion, predictive models, spatial and spectral resolutions, species spatial spread, spectral signature.

INTRODUCTION

Human activities such as international trade and travel promote biological invasions by accidentally or deliberately dispersing species outside their native biogeographical ranges (Lockwood, 2005; Alpert, 2006). Invasive species are now viewed as a significant component of global change and have become a serious threat to natural communities (Mack *et al.*, 2000; Pyšek & Richardson, 2010). The ecological impact of invasive species has been observed in all types of ecosystems. Typically, invaders can change the niches of co-occurring species, alter the structure and function of ecosystems by degrading native communities and disrupt evolutionary processes through anthropogenic movement of species across physical and geographical barriers (D'Antonio & Vitousek, 1992; Mack *et al.*, 2000; Richardson *et al.*, 2000; Levine *et al.*, 2003; Vitousek *et al.*, 2011).

Concerns for the implications and consequences of successful invasions have stimulated a considerable amount of research. Recent invasion research ranges from the developing testable hypotheses aimed at understanding the mechanisms of invasion to providing guidelines for control and management of invasive species.

Several recent studies have used hyperspectral remote sensing (Underwood *et al.*, 2003; Lass *et al.*, 2005; Underwood

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& Ustin, 2007; Asner *et al.*, 2008a,b; Andrew & Ustin, 2009, 2010; Ustin & Gamon, 2010; Vitousek *et al.*, 2011) to assess current spatial distribution and future dispersal of invasive plants at local, regional and global scales. In this review article, we draw attention to hyperspectral remote sensing investigations that have resulted in new ecological insights for plant invasion that would not otherwise have been possible.

We report what remote sensing can offer for invasion ecologists and review recent progress made in invasion research using hyperspectral remote sensing. First, we give a general overview of hyperspectral remote sensing for readers who are not familiar with this field. Second, we discuss the strengths and opportunities of using hyperspectral remote sensing for mapping the spatial spread of invasive species. Third, we focus on the key challenges in getting the best use of hyperspectral remote sensing for invasion research including: (1) the trade-off between spatial and spectral resolutions and classification accuracy, (2) using time series to incorporate phenology for improving mapping accuracy and determining the best time for image acquisition, (3) the potential of biogeochemical and physiological properties in hyperspectral spectral reflectance for distinguishing invasive species from co-occurring vegetation and for tracking the dynamic changes of ecosystems caused by invasion, and (4) the value of hyperspectral data as a predictor or response variable for quantitative models developed for predicting the future spread of invasive species, thus providing timely information for invasion risk analysis.

A BRIEF OVERVIEW OF HYPERSPECTRAL REMOTE SENSING

The terms hyperspectral imaging, imaging spectroscopy and imaging spectrometry are interchangeable in the remote sensing literature. Hyperspectral remote sensors acquire images across many, narrow contiguous spectral bands mainly throughout the visible, near-infrared and mid-infrared portions of the electromagnetic spectrum (Vane & Goetz, 1993). Typically, hyperspectral sensors measure the reflected spectrum at wavelengths between 350 and 2500 nm using 150–300 contiguous bands of 5- to 10-nm bandwidths (Ustin *et al.*, 2004). Recent scanners support even higher spectral resolutions in the subnanometer range. Absorption of light in the electromagnetic spectrum by plant pigments and other types of molecules produces a unique spectral reflectance signature which is in turn influenced by the leaf chemistry and its three-dimensional structure (Ustin *et al.*, 2004). The theoretical concept involved here is that each plant species should possess a unique molecular makeup at the foliar level. With a hyperspectral sensor, many narrow bands can capture a range of absorption features including leaf or canopy biochemical constitutes such as chlorophyll, carotenes, water, nitrogen, cellulose and lignin (reviewed in Ustin *et al.*, 2004). As leaves and plant species vary in the concentration of their biochemical constitutes, the reflectance spectra vary as well. It is expected that variations in spectral signatures (shape and the depth of the shape) should be found across environmental gradients or taxonomic lines (Kokaly *et al.*, 2009; Ustin *et al.*, 2009) (Figs 1 & 2).

Currently, spectral information is provided by several hyperspectral sensors such as Hyperion, Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), Compact Airborne Spectrographic Imager (CASI), Airborne Imaging Spectroradiometer for Applications (AISA) and HyMap (from HyVista, Castle Hill, Australia). All of these sensors have been used to detect of invaders at the species level (Clark *et al.*, 2005; Andrew & Ustin, 2006, 2008, 2009; Lawrence *et al.*, 2006; Miao *et al.*, 2006; Pengra *et al.*, 2007; Underwood & Ustin, 2007; Asner *et al.*, 2008a,b; Hestir *et al.*, 2008; Pu *et al.*, 2008; Narumalani *et al.*, 2009). We summarize hyperspectral sensor information in terms of the types of sensors, platforms, sensor characteristics, availability and source of data in Table 1. Further, we report a few recent case studies to illustrate the

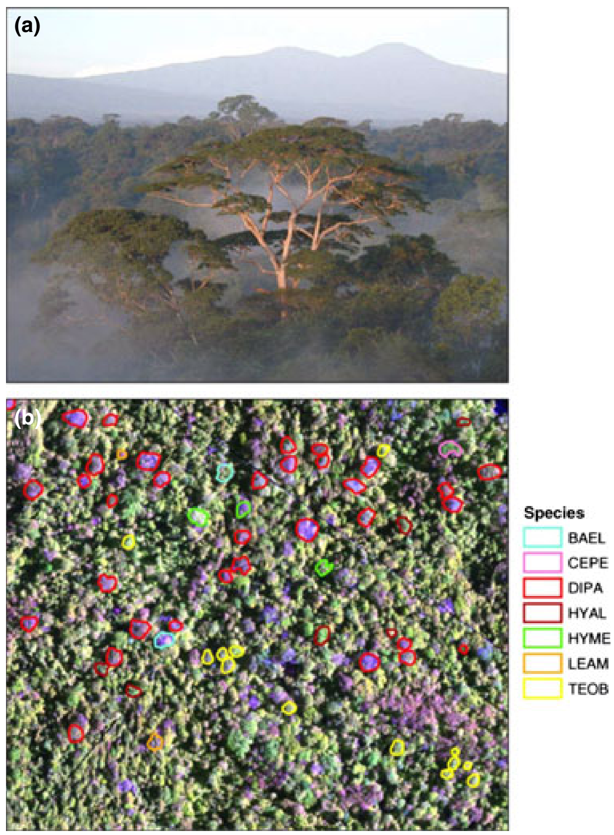

Figure 1 (a) View of old-growth Tropical Wet Forest at the La Selva Biological Station. The canopy-emergent tree in the foreground is *Balizia elegans*. (b) Example of 1.6-m spatial resolution HYDICE hyperspectral imagery over old-growth canopy [red: 1651 nm (SWIR2), green: 835 nm (NIR), blue: 661 nm (red)] with overlaid individual tree crown polygons. Species code: BAEL – *Balizia elegans*, CEPE – *Ceiba pentandra*, DIPA – *Dipteryx panamensis*, HYAL – *Hyeronima alchorneoides*, HYME – *Hymenolobium mesoamericanum*, LEAM – Lecythis ampla, TEOB – *Terminalia oblonga*. Map scale is 1:3000 (reproduced from Clark *et al.*, 2005). This figure is available in colour online.

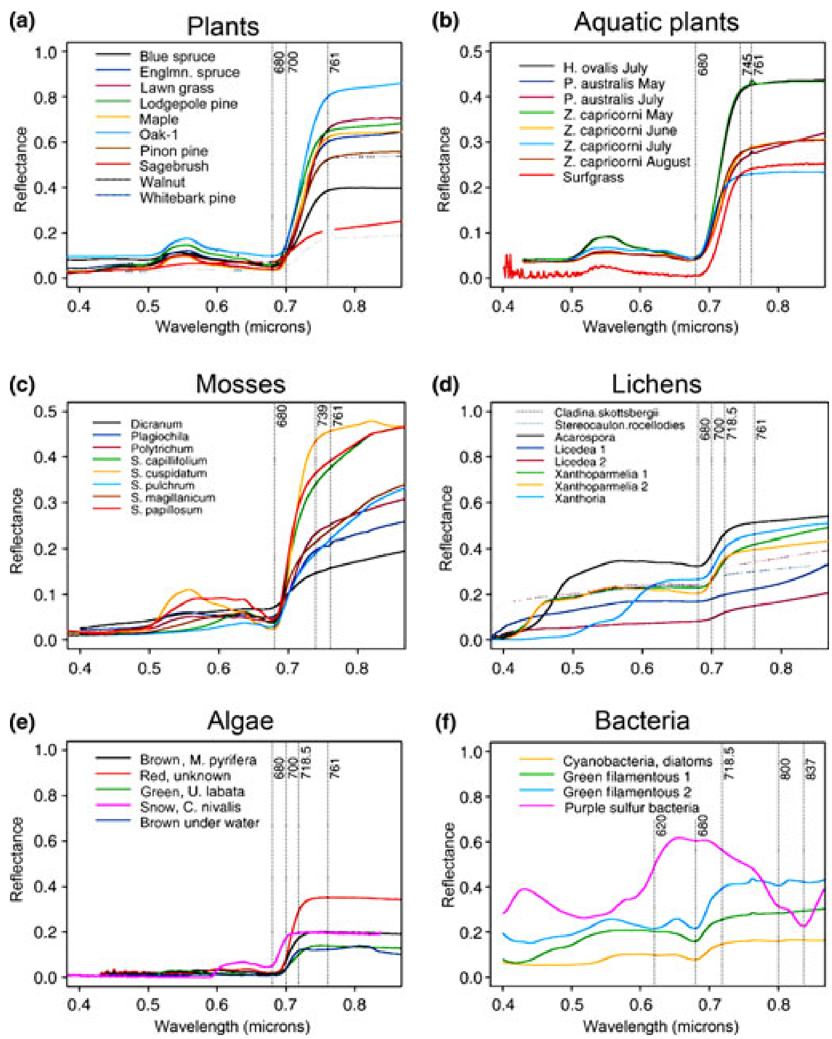

Figure 2 Major groups of photosynthetic organisms have distinct spectral signatures in the visible and near infrared spectrum, making them potentially distinguishable with hyperspectral remote sensing (reproduced from Kiang *et al.*, 2007). This figure is available in colour online.

utility of hyperspectral remote sensing in invasion research in Table 2.

Although hyperspectral remote sensing has a relatively short history (< 30 years, Vane & Goetz (1988)) compared to other types of remote sensing such as aerial photographs, hyperspectral sensors have been very effective for mapping the spatial extent of native and non-native species across all types of communities and ecosystems. However, there are also drawbacks associated with hyperspectral remote sensing. First, the high cost of acquiring hyperspectral data. A typical cost for hyperspectral data varies between \$60,000 and \$100,000 for a 20×20 km area at 2- to 3-m spatial resolution (Lass *et al.*, 2005). Therefore, data acquisition could become a problem for some underfunded institutions or individual research laboratories. Second, the technical aspects of processing hyperspectral data are complex, and the whole process might be outside the expertise of most ecologists. However, many private services such as HyVista Corporation can provide processed data for ecologists who need the information but lack the data-processing expertise. This also can be helped by conducting interdisciplinary research between ecologists and geographers at a much lesser cost. Third, the huge volume of hyperspectral image data requires a large data storage capacity and can be time intensive to process. Fourth, since most current hyperspectral sensors are airborne, their global coverage is limited. With the recent advent of satellite-based hyperspectral sensors such as Hyperion, however, this should become less of an issue in the next decade.

HYPERSPECTRAL REMOTE SENSING FACILITATES INVASION RESEARCH

In general, invasion ecologists know the possible regions where an invasive species may be found, but detailed maps are usually unavailable to them. The same situation applies to conservation biologists and land managers who are directly involved in the control and management of invasive species and the protection of natural ecosystems. Early detection and mapping of the extent of rapidly spreading invasive populations are critical for informing management priorities, including eradication efforts. Unfortunately, it is very time-consuming and expensive to repeatedly detect, monitor and document the

Table 1 Hyperspectral sensor information in terms of the types of sensors, platforms, sensor characteristics, source of data and availability.

Sensor	Sensor characteristics	Source of data	Availability (reference site)
Airborne Imaging Spectroradiometer for Applications (AISA) hyperspectral imagery	492 bands, spectral range: 395- to 2503-nm, spatial resolution: 75 cm–4 m	Specim, Spectral Imaging, Ltd – Finland	http://www.specim.fi/products/aisa-airborne-hyperspectral-systems/aisa-series.html
Airborne Visible InfraRed Imaging Spectrometer (AVIRIS)	224 bands, spectral range: 400- to 2500-nm, spatial resolution: 3.5 m	National Aeronautics and Space Administration (NASA) – USA	http://aviris.jpl.nasa.gov/
Compact Airborne Spectrographic Imager (CASI)	288 bands, spectral range: 430- to 870-nm, spatial resolution: 3 m	ITRES – Canada	http://www.itres.com/
EO-1 Hyperion hyperspectral sensor (Spaceborne)	220 bands, spectral range: 357- to 2576-nm, spatial resolution: 30 m	National Aeronautics and Space Administration (NASA) – USA	http://eo1.gsfc.nasa.gov/Technology/Hyperion.html
HyMap (Hyperspectral Mapper, Airborne)	126 bands, spectral range: 450- to 2500-nm, spatial resolution: 3 m	HyVista – Integrated Spectronics Pty Ltd – Australia	http://www.hyvista.com/

spatial distribution of invasive plants by field-based surveys for even a region as small as a county. Moreover, concerning field sampling of plant species, three major problems may arise. First of all, observation bias could lead to an underestimate of the presence of a species in the field because of existing taxonomic issues such as the affinity of certain species. It happens when species or subspecies are lumped together or split apart or when they are renamed as previously named taxa or new taxa (Bacaro *et al.*, 2009). Second, field surveys are rarely repeated for a large study area; thus, the temporal dynamics of invasive species are not examined. Third, as provocatively stressed by Palmer & White (1994), the ratio between biologists who directly conduct the field work for compiling species lists and the number of existing plant species is very low. As a result, maps generated by hyperspectral data are much more comprehensive than field surveys (Gillespie *et al.*, 2008). This is especially true when the study areas are remote and/or have rugged terrains. Moreover, hyperspectral data provide great opportunities to go 'back in time' with archived data to document invasion patterns which may improve projections of future spread.

Spatial resolution and classification accuracy

Remote sensing has been used to map invasive plants in the past decade, but its effectiveness has been hindered by the relatively coarse resolution of many earlier systems (Carter *et al.*, 2009). The popular multispectral Landsat images are collected with a spatial resolution of 30 × 30 m pixels, which is rarely detailed enough to identify invasive species. However, Landsat images and other remote sensors with moderate spatial and spectral resolution can be effective when the infested area is large, habitat conditions are more homogeneous and the targeted species have a distinct phenology or visual characteristics (Everitt *et al.*, 1995, 1996; Bradley & Mustard, 2005; Groeneveld & Watson, 2008; Wilfong *et al.*, 2009). In recent years, however, remotely sensed data of very fine resolution have become available through dozens of new high spatial resolution satellites and many airborne hyperspectral sensors with high spectral resolution that record hundreds of wavelength bands. For example, the GeoEye-1 satellite launched in 2008 collects data at 41-cm resolution (in the panchromatic channel), currently the finest spatial resolution available from commercial satellites.

Spatial resolution used in remote sensing is critical because it determines the level of accuracy of classification of objects using the least amount of data. Low spatial resolution can hardly discriminate objects on the ground resulting in lower classification accuracy. In general, finer spatial resolution (more pixels) increases classification accuracy, but at the same time, smaller pixels increase spectral variance resulting in decreased spectral separability of classes (Nagendra & Rocchini, 2008). As suggested by Nagendra (2001), the ratio of spatial resolution to the size of the objects being classified plays an important role in achieving an adequate classification. In most invasion studies, the objects that we are dealing with are tree crowns, herbaceous plant species or patches of shrubs or grasses. When pixel dimensions shrink below the size of the object studied, for instance, to a point where individual pixels are smaller than the size of individual tree crowns, then there is an increase in the variability of spectral signatures on the same individual tree (Ricotta *et al.*, 1999; Song & Woodcock, 2002; Rocchini & Vannini, 2010). This variability is because of differences in shading, and separate imaging of leaves and bark, which can make it harder to identify representative signatures of different species (Nagendra, 2001; Wulder *et al.*, 2004). In a case study in southern Florida, Fuller (2005) concluded that multispectral IKONOS imagery with 4-m spatial resolution was not appropriate for mapping *Melaleuca quinquenervia*, an invasive tree species because of the high levels of internal

Table 2 Recent case studies illustrating the utility of hyperspectral remote sensing in invasion research according to habitat type, invasive plant, study area and classification mode.

Habitat type	Invasive species	Study area	Classification model	Reference
Crops	Canada thistle (*Cirsium arvense*), Russian olive (*Elaeagnus angustifolia*)	North Platte River, Nebraska	Spectral angle mapping	Narumalani *et al.* (2009)
Mixed forest–suburban areas	24 introduced tree species	Hawaii Islands	Canopy spectral signatures profiling	Asner *et al.* (2008a)
Shrubland, chaparral, grassland	Iceplant (*Carpobrotus edulis*), jubata grass (*Cortaderia jubata*), and blue gum (*Eucalyptus globulus*)	Vandenberg Air Force Base, California	Quality Assurance analysis	Underwood & Ustin (2007)
River, riparian vegetation	Salt cedars (*Tamarix chinensis*, *T. ramosissima*, *and T. parvifolia*)	Humboldt River, Nevada	Artificial neural networks and linear discriminant analysis	Pu *et al.* (2008)
Grasslands	Yellow starthistle (*Centaurea solstitialis*)	California's Central Valley	PCA, unconstrained LSMMs	Miao *et al.* (2006)
Pastures, grasslands, natural forests	Guava (*Psidium guajava*)	Galapagos Islands, Ecuador	Spectral unmixing	Walsh *et al.* (2008)
Wetlands	*Phragmites australis*	Great Lakes, Wisconsin	Spectral Correlation Mapper (SCM) algorithm	Pengra *et al.* (2007)
Mountain rain forests	*Myrica faya*	Hawaii Volcanoes National Park	Remotely sensed Photochemical and Carotenoid Reflectance indices (PRI, CRI)	Asner *et al.* (2006)
Wetlands	Perennial weed (*Lapidium latifolium*), water hyacinth (*Eichhornia crassipes*), Brazilian waterweed (*Egeria densa*)	Sacramento-San Joaquin Delta	Binary decision tree, spectral angle mapping	Hestir *et al.* (2008)
Mixed riparian zones and sagebrush-steppe vegetation	Leafy spurge (*Euphorbia esula*)	Swan Valley, Idaho	Mixture Turned Matched Filtering algorithm	Glenn *et al.* (2005)

variability within tree canopies which make it difficult to delineate and classify individual tree crowns. The author concluded that IKONOS imagery is most likely to be useful for detecting large, dense stands of this invasive tree species. When detecting low-density occurrences (< 50%) of *Melaleuca*, the IKONOS multispectral imagery was no more effective than methods of aerial photographic interpretation. Further, the study recommended using hyperspectral sensors that employ many narrow bands to improve spectral separability, thus leading to an accurate mapping of this invasive species even at a lower density.

Another interesting study carried out by Carter *et al.* (2009) compared the efficacy for discriminating tamarisk (*Tamarix* spp.) populations near De Beque, Colorado, USA among high spatial resolution, multispectral satellite imagery (2.5 m QuickBird) and 30-m hyperspectral (EO-1 Hyperion) or multispectral (Landsat 5 Thematic Mapper, TM5) data. The authors assessed classification accuracy using error matrix and the K_{hat} coefficient of agreement (representing the extent to which a given classification procedure improved classification accuracy relative to a random classifier). Their study concluded that multispectral QuickBird data with 2.5-m spatial resolution proved to be more effective in tamarisk mapping than either TM5 or hyperspectral data at 30-m spatial resolution. The higher spectral resolution of Hyperion did not improve the classification accuracy over the results of QuickBird. The authors suggested that within-pixel spectral mixing reduced the utility of high spectral resolution. There were no ground plots containing 80–100% tamarisk cover within a spatial extent comparable to a Hyperion pixel (30 m), which made it impossible to identify a pure signal from the invasive species at that spatial resolution.

Moreover, an extended and comparative study was carried out by Hamada *et al.* (2007) to detect tamarisk in the riparian habitat of southern California using very high spatial (0.5 m) and spectral (with 120 spectral channels between 394 and 8904 nm and a 4-nm average band width) resolution imagery acquired using a Surface Optics Corporation (SOC) 700 hyperspectral sensor. The highest correct detection rate reached 90% with a pixel size of 25 m^2. Their results further confirm that high spatial resolution imagery often contains greater intraspecies spectral variability when patches are much larger than the pixel size.

Spectral resolution and classification accuracy

When aiming at mapping individual species, a high spectral resolution is particularly useful when the targeted species has a low distribution density or exhibits a scattered spatial pattern in a heterogeneous community. Remotely sensed data with high spectral resolution can be used to distinguish different plant species based on their unique reflectance properties. However, different phenological states such as flowering and senescence combined with different physical structures in leaf and canopy can create intraspecies variation that contributes to overlapping spectral signatures between co-occurring species.

Hestir *et al.* (2008) presented three case studies using airborne hyperspectral remote sensing to develop regional-scale monitoring of invasive aquatic and wetland weeds in the Sacramento–San Joaquin Delta: the terrestrial Riparian weed, perennial pepperweed (*Lepidium latifolium*); the floating aquatic weed, water hyacinth (*Eichhornia crassipes*); and the submerged aquatic weed, Brazilian waterweed (*Egeria densa*). HyMap, an airborne hyperspectral imager that collects 126 bands at bandwidths from 10 to 20 nm, was used in their study. The spatial resolution of the data is 3 m, with a swath width of 1.5 km. The authors achieved the user's and producer's accuracies for perennial pepperweed detection of 75.8% and 63.0%, respectively; for water hyacinth detection of 89.8% and 69.1% and for Brazilian waterweed detection of 92.1% and 59.2%. Their study suggests that perennial pepperweed and water hyacinth both exhibited significant spectral variation related to plant phenology.

Lawrence *et al.* (2006) mapped two invasive species leafy spurge (*Euphorbia esula*) and spotted knapweed (*Centaurea maculosa*) at two study sites in Madison County, Montana, where infestation occurred at widely varying densities and phenological stages. Most study areas were not uniform, but contained a mixture of invasive species and co-occurring vegetation, thus making the mapping of targeted species more difficult. The authors used a 128-band hyperspectral imagery obtained by the Probe-1 sensor and a Random Forest classification algorithm to map the spatial extent of this two herbaceous invasive species. High overall accuracy for both species was achieved (84% for spotted knapweed and 86% for leafy spurge), demonstrating the advantage of using hyperspectral imagery for invasive species mapping in a heterogeneous community.

The trade-off between spatial and spectral resolution and classification accuracy was discussed by Underwood & Ustin (2007). The authors carried out a comparative study using different spatial and spectral resolution for mapping three invasive species, iceplant (*Carpobrotus edulis*), jubata grass (*Cortaderia jubata*) and blue gum (*Eucalyptus globules*) in the coastal California. Four hyperspectral AVIRIS images with different combinations of spatial and spectral resolutions were employed in their study. The authors found that the overall accuracy was highest (75%) with imagery possessing high spectral resolution (174 bands), suggesting that higher spectral resolution images tend to yield maps with a higher overall accuracy than multispectral images (42% with six bands and 4-m resolution). Further, the authors evaluated mapping accuracy in the context of community heterogeneity which represents species richness, diversity or species percentage cover. Their study found: (1) high spectral but low spatial resolution imagery is a better choice when there are monotypic stands of invaders within communities with lower heterogeneity; (2) high spectral resolution imagery coupled with high spatial resolution works better when the invader distribution is limited within communities; (3) fine or coarse spatial resolution data might not make any differences when there is higher heterogeneity within the communities.

Using time series to incorporate phenology in invasion research

Currently, studies are moving towards the use of multidate remotely sensed images to aid the detection and mapping of invasive species following plant phenological changes at the same study sites. The uniqueness in phenology of some invasive species provides a sound basis for identifying spectral differences between targeted species and co-occurring native vegetation (Williams & Hunt, 2004; Peterson, 2005; Ge *et al.*, 2006; Andrew & Ustin, 2008; Evangelista *et al.*, 2009; Singh & Glenn, 2009). Invaders such as downy brome (*Bromus tectorum*), leafy spurge (*Euphorbia esula*), yellow starthistle (*Centaurea solstitialis*) and pepperweed (*Lepidium latifolium*) are good examples in this regard because of their possession of distinct timing for peak biomass and blooming (Fig. 3).

Noujdina & Ustin (2008) studied downy brome invasion pattern using multidate AVIRIS data in south-central Washington, USA. The authors compared detectability of downy brome from single-date and multidate AVIRIS data using a mixture-tuned matched filtering algorithm for image classification. They concluded that the use of multidate data increased the accuracy of downy brome detection in the semi-arid rangeland ecosystems. The mapping accuracy is a direct result of clear spectral differences controlled by phenological dissimilarities between downy brome and surrounding vegetation (Fig. 4).

Leafy spurge is a Eurasian exotic plant species invading the north central and western United States. When it is in bloom,

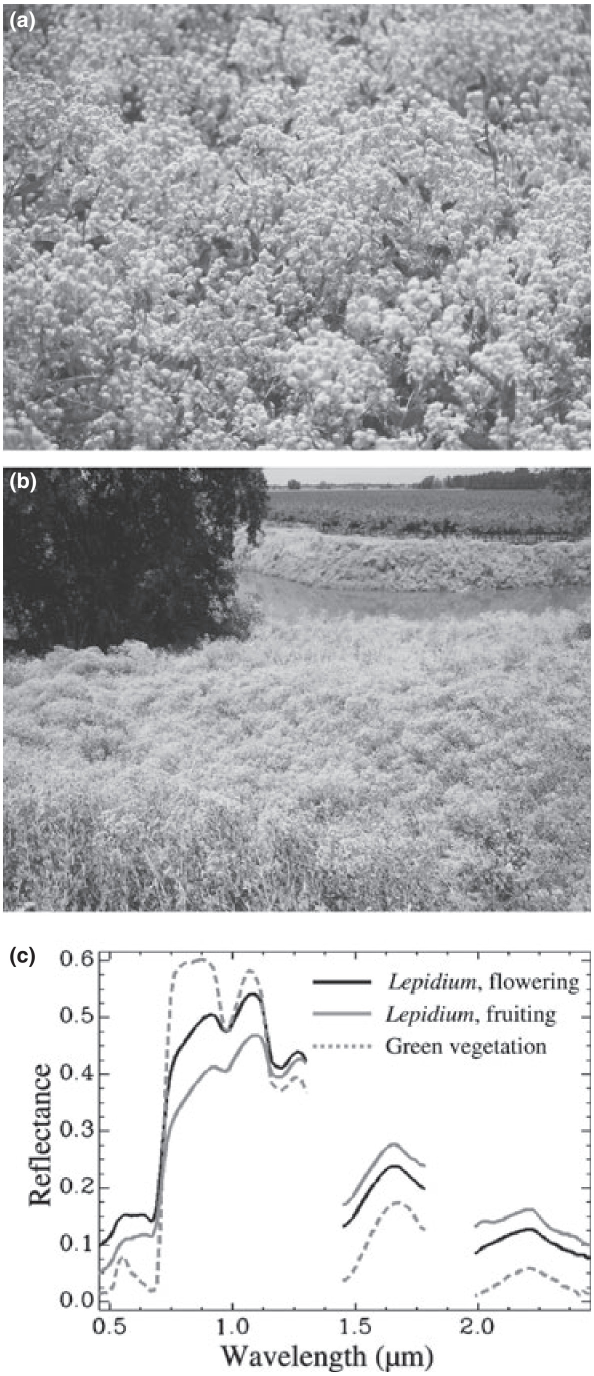

Figure 3 Flowering and fruiting phenologies of *Lepidium latifolium* (perennial pepperweed) can be spectrally distinct from co-occurring species. (a) Photograph of *L. latifolium*, highlighting the thick, white inflorescence. (b) A dense infestation of *Lepidium* in the Sacramento–San Joaquin River Delta. (c) Field spectra of flowering and fruiting phenologies of *Lepidium*, along with a typical reflectance spectrum of green vegetation (reproduced from Andrew & Ustin, 2008).

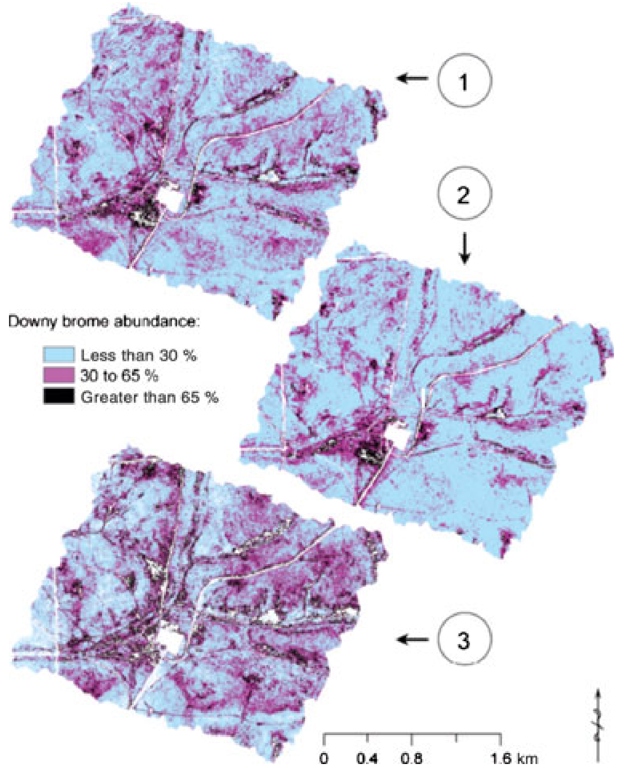

Figure 4 The maps of downy brome (*Bromus tectorum*) abundance predicted by the analysis of three different data sets. (1) Multitemporal spectral stack; (2) July 2000 spectral data; and (3) May 2003 data. The overall accuracy coefficients for the three downy brome occurrence maps were 0.81 for multitemporal data set, and 0.70 and 0.72 for 2000 and 2003 data sets (reproduced from Noujdina & Ustin, 2008). This figure is available in colour online.

its yellow green bracts provide a distinct spectral characteristic for assessing its spatial spread remotely (Everitt *et al.*, 1995; Anderson *et al.*, 1999; O'Neill & Ustin, 2000; Williams & Hunt, 2002, 2004; Kokaly *et al.*, 2004; Mitchell & Glenn, 2009). Glenn *et al.* (2005) used HyMap hyperspectral data collected over 2 years to detect the infestation of leafy spurge in Idaho, USA. A slight difference in leafy spurge reflectance was found between the 2002 and 2003 images, which was attributed to differences in leafy spurge bloom and time of the image acquisition. The authors also performed accuracy assessments for each year's classification data and found that user's accuracies were all above 70%, suggesting image processing methods were repeatable between years.

Significant changes in phenology can help ecologists and biogeographers determine the best time to discriminate invasive species remotely. Imagery acquired during key phenological events improves overall mapping accuracy. For example, Laba *et al.* (2005) tried to determine the optimal dates for discriminating invasives including purple loosestrife (*Lythrum salicaria*), common reed (*Phragmites australis*) and cattail (*Typha* spp.) in upstate New York. Weekly radiometric data were collected at three sampling sites from June to October and analysed using derivative spectral analysis methods. The authors identified August as the best month for differentiating plant communities dominated by these three invasive species based on significant changes in their phenology. For example, while purple loosestrife has a clear characteristic reddish-purple colour in early August, common reed blooms late with a brown to whitish tassels on the top of the stem and cattail plants typically bloom early in the summer and have brown inflorescences in August and September.

Another study on the phenological assessment of an invasive species, yellow starthistle, was carried out by Ge *et al.* (2006) using CASI. The authors compared the spectral characteristic of canopy components at different flowering stages including stems, buds, opening flowers and post-flowers. They calculated spectral dissimilarity and spectral angles for each stage and found significant spectral differences at different flowering stages of yellow starthistle. Peak flowering stage was identified as the best time period for differentiating the spectral signature of this invasive species. Thus, imagery acquired during peak flower of this invasive species could improve its mapping accuracy substantially.

The potential of biochemical and physiological properties in hyperspectral reflectance

Recently, biochemical and physiological properties of plant species have been investigated to distinguish invasive species from native species and to determine the compositional changes of native ecosystems caused by invasions using hyperspectral remote sensing (Asner & Vitousek, 2005; Hughes & Denslow, 2005; Funk & Vitousek, 2007; Asner *et al.*, 2008a,b). In this case, the advantages of hyperspectral data are twofold: first, unique spectral reflectance derived from biochemical and physiological properties of plant species yields accurate identification and mapping of targeted species; second, hyperspectral data can adequately produce quantitative estimates of biophysical absorptions which can be used to enhance the understanding of ecosystem functioning and properties (Ustin *et al.*, 2004; Vitousek *et al.*, 2011).

The aforementioned studies have shown that the observed differences in canopy spectral signatures are linked to the relative differences in measured leaf pigments, nutrients, water contents and structural (specific leaf area) properties. Asner *et al.* (2008a) used AVIRIS to analyse the canopy hyperspectral reflectance properties of 37 distinct species, including both native and introduced species in Hawaii. They concluded that the AVIRIS reflectance and derivative reflectance signatures of Hawaiian native trees are generally unique from those of introduced trees (Fig. 5). This suggests that the basic spectral separability of major groups of species appears tractable and useful in identifying the spatial extent of targeted species. Furthermore, biogeochemical changes found at the foliar and canopy levels indicate not only where invasion has occurred, but also the invasion effects at the ecosystem level.

The spectral differences between introduced and native species can be directly used to study the impact of invasive species on native ecosystems. Asner & Vitousek (2005) used AVIRIS data and photon transport modelling to determine how two distinct invasive species, a nitrogen-fixing tree (*Myrica faya*) and an understory herb (*Hedychium gardnerianum*) altered the chemistry of forest canopies across a Hawaiian montane rain forest. They found that *M. faya* doubled canopy nitrogen concentration and water content in the invaded areas, whereas the *H. gardnerianum* significantly reduced nitrogen concentration and increased aboveground water content. The results of this study directly indicate the biogeochemical impact on the rain forest caused by invasive species.

Further, in a similar study area, a time series of Hyperion data was used to study the dynamic changes of Hawaiian rain forests (Asner *et al.*, 2006). The authors compared the structural, biochemical and physiological characteristics of an invasive tree *M. faya* and native *Metrosideros polymorpha*. Using nine scenes spanning from July 2004 to June 2005,

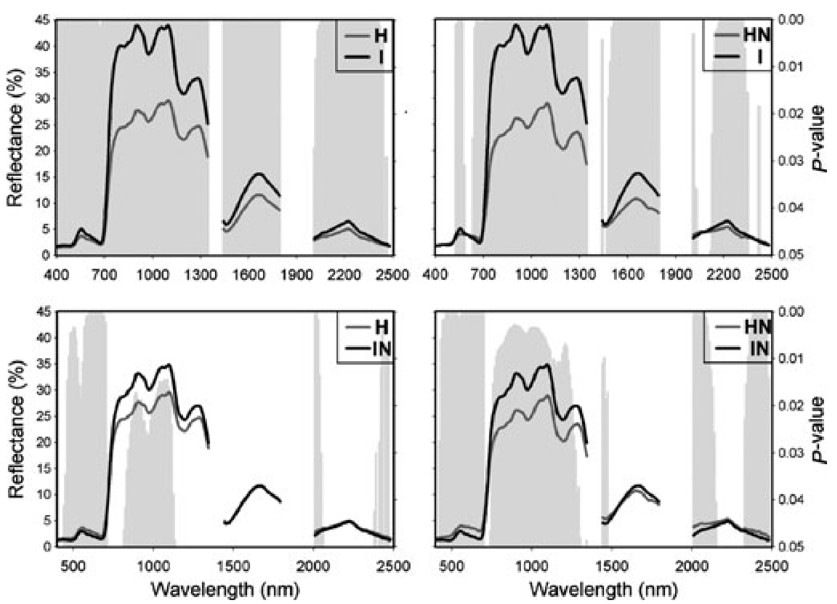

Figure 5 Mean reflectance of Hawaiian non-fixing (H), Hawaiian nitrogen-fixing (HN), introduced non-fixing (I), and introduced nitrogen-fixing (IN) species, with band-by-band *t*-tests showing significant differences in grey bars (*P*-values ≤ 0.05) (reproduced from Asner *et al.*, 2008a).

including a transition from drier/warmer to wetter/cooler conditions, the authors successfully identified basic biological mechanisms favouring the spread of an invasive tree species and provided a better understanding of how vegetation–climate interactions affect plant growth during the invasion process.

Hyperspectral data can inform predictive models of invasion

Developing spatially explicit distribution models for predicting the future spread of invasive species is a critical research area for invasion ecologists. Many predictive models have been developed for tracking invasive species in time and space to provide timely information for resource managers and policy makers who need accurate species distribution maps for invasion risk analysis. Typically, these predictive models include generalized additive models, logistic regression, classification and regression tree model, random forest, maximum entropy and bioclimatic envelope models (Peterson, 2003; Thuiller *et al.*, 2005; Elith *et al.*, 2006; Evangelista *et al.*, 2008; Stohlgren *et al.*, 2010). Climatic, topographical and edaphic variables along with vegetation indices have been used as predictor variables for these predictive statistical models. Remotely sensed data, especially data derived from Landsat images, have been parameterized in predicting the future spread of invasive species (Rouget *et al.*, 2003; Morisette *et al.*, 2005; Peterson, 2005, 2006; Rew *et al.*, 2005; Bradley & Mustard, 2006; Hoffman *et al.*, 2008; Evangelista *et al.*, 2009; Stohlgren *et al.*, 2010). However, the use of hyperspectral data for invasive risk analysis is not yet widespread even though hyperspectral data are a valuable input for quantitative models developed for invasion research.

One example of hyperspectral data used for invasion risk assessment is carried out by Andrew and Ustin (2009). They developed a habitat suitability model to assess the ability of advanced remote sensing data for evaluating habitat susceptibility to invasion by pepperweed (*Lepidium latifolium*) in California's San Francisco Bay/Sacramento-San Joaquin River Delta. Their study used both predictor and response variables derived from remote sensing. In particular, the present/absent data of the invasive species, pepperweed were extracted from a hyperspectral image. Predictor variables were derived from a high resolution light detection and ranging (LiDAR) digital elevation model (DEM). An aggregated classification and regression tree model was used to evaluate habitat suitability of this invasive species. Their study found that pepperweed invaded relatively less stressful sites along the inundation and salinity gradients. Further, the authors suggested that hyperspectral data sets are sufficient for species distribution modelling and deserve an increased attention from ecologists.

The potential of using hyperspectral data in species distribution modelling cannot be underestimated. This is especially relevant in invasion research considering that many studies including the ones mentioned in this review have produced high-quality maps of invasive species in both terrestrial and aquatic habitats. Those maps are valuable inputs for developing spatially explicit distribution models for invasion risk analysis. Furthermore, we stress that species distribution models based on hyperspectral data are at very different scales from typical distribution models (which are usually at regional scale and related to climate, occasionally at landscape scale related to land use) to fine-scale studies (which are related to habitat conditions and biotic interactions). The addition of fine-scale distributional relationships may provide additional key insights as to what influences species distribution at local scales. This information can also potentially test mechanistic understanding of local invasive species distribution developed from field studies.

SUMMARY

As indicated by the case studies discussed in previous sections, hyperspectral remote sensing holds great promise for invasion research. Our review shows that investigations using hyperspectral remote sensing have resulted in new ecological insights for plant invasion that would not otherwise have been possible. Despite its proven utility in mapping and modelling the distribution of invasive species, hyperspectral remote sensing is underused by invasion ecologists. This may be owing to the following two reasons suggested by Turner *et al.* (2003): first, the misperception that the spatial scales used in remote sensing systems do not match the scales addressed by ecologists and conservation biologists; second, the lack of interdisciplinary training for both ecologists and geographers in general. Therefore, there is still a gap in our current knowledge about the biogeography of biological invasion which presents an excellent opportunity for interdisciplinary research. The direct benefits of this type of interdisciplinary research are apparent: remotely sensed data can provide a baseline of invasive species distributions for future monitoring and control efforts; furthermore, information on the spatial distribution of invasive species can help land managers to develop targeted eradication efforts and long-term conservation plans.

In this review, we state that hyperspectral remote sensing for invasion research is critical and much needed, because remotely sensed information can provide a synoptic and holistic insight into the process of invasion at various spatial and temporal scales. However, we also emphasize that data collected from space simply cannot replace the information gathered through ground investigations. By combining these two data sources, invasion ecologists will have much reliable information on hand to advance research in tackling the success of introduced species across all types of ecosystems and biomes.

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BIOSKETCHES

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