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Using Remotely Sensed Imagery for Forest Resource Assessment and Inventory

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1. Introduction

Forests are complex ecosystems that develop over centuries through the interactions between organisms and biogeochemical cycles of elements occurring in the soil-atmosphere continuum. The biomass and structure of a forest stand is involved in several ecosystem processes and has been used as an indicator of forest health and productivity. The forest biomass is a key component of the carbon cycle, as forests represent large carbon sources and sinks (Skole & Tucker, 1993). Tree canopy height and area are highly correlated with biomass and are important inputs in forest productivity models (Drake, 2001). The variation of forest biomass production has been related to variations in canopy light absorption since the amount and spatial distribution of vegetation, directly affects light availability in forests. Forest stand factors that determine light absorption include: amount of leaf area, crown and canopy structure, phenology, and leaf optical properties (Jarvis and Leverenz, 1983). The amount of leaf area, measured through the leaf area index (LAI), is considered a key parameter of ecosystem processes (Asner and Wessman, 1997). Several forest ecosystem processes are strongly controlled by LAI including interception of light (Machado & Reich, 1999) and precipitation (Van Dijk & Bruijnzeel, 2001), gross primary productivity (Jarvis & Leverenz, 1983), transpiration (Granier et al., 2000), and soil respiration (Davidson et al., 2002). LAI is also related to other important ecological processes such as evapotranspiration, CO_2 and water exchange with the atmosphere, nutrient cycling and nutrient storage in plants (Dougherty et al. 1995). Therefore, measurements of forest biomass and structure are critical in the study of ecosystems for many applications including management of forest plantations, wildlife and biodiversity, fire modeling, and carbon sequestration among others.

Traditionally, the assessment of forest structure and growth has been done by measuring forest canopy attributes such as tree canopy dimensions, height and LAI in the field using hand-held equipment including leaf area meters, height poles, clinometers and measure tapes. Although field-based methods can be highly accurate, they are typically limited in scope to either mapping at plot scales or sampling sites at the landscape scale. Because of the expense of conducting detailed forest inventories over large areas, considerable research has focused on developing tools to estimate forest canopy attributes using remote sensing techniques. Historical aerial photos have proven useful, but analysis has generally been done manually. With new satellite sensors and improved computing power and analytical software, remote sensing is becoming an important tool for forest cover mapping, environmental monitoring, and ecological process assessments from global, regional, and landscape levels (Plummer, 2000).

This chapter is a review of the remote sensing technologies currently used to achieve more accurate forest resource inventory and assessment at landscape and regional scales. The review had three main objectives. The first objective was to describe remote sensing principles and technology development for forest research worldwide. The second objective was to present practical applications of remote sensing technologies used to characterize forest structure and health at the stand and individual-tree levels. The third objective was to present strategies for effective use of remote sensing technologies to improve management of forests worldwide.

2. Remote sensing technologies for forest research

The basic principle in using remote sensing is based on the selective nature of radiation absorption by vegetation canopies, resulting in unique spectral signatures that describe distinctive patterns of short-wave (visible and infrared) radiation reflectance. The reflectance spectrum of green vegetation is characterized by low reflectance in the red region (0.6 - 0.7 μm), associated with chlorophyll absorption, and strong near infrared (NIR) reflectance (0.7 -1.2 μm) related to internal leaf structure (Jensen, 2000; Roberts et al., 1997). Satellites may be either active or passive and are designed to capture reflectance from various regions of the electromagnetic spectrum as multispectral bands. While active satellite sensors transmit signals which are detected or emitted back at the instrument after hitting the earth surface, passive sensors do not transmit energy signals, but rather only detect reflected energy from earth in the visible and infrared regions. Available multispectral satellite imagery from passive sensors over the last 30 years and improved satellite imaging technologies over the last 10 years have increased the capabilities to describe spatial and temporal dynamics of vegetation characteristics at numerous scales. Multispectral imagery from medium resolution sensors, such as Landsat (30-m pixel resolution) (Curran et al., 1992, Baugh and Groeneveld, 2006; Xu, 2007) and Spot (5-m pixel resolution) (Soudani et al., 2006), have been used to assess vegetation conditions and phenological changes in forested areas at regional and landscape scales. Günlü et al. (2008) integrated the analysis of Landsat imagery with conventional forest inventory measurements and ecological and physiographic information to produce site quality index maps for various temperate forest species in Turkey. However, the spatial resolution of medium resolution satellites does not allow resolving forest stands and individual trees. Fine resolution satellites such as Ikonos, QuickBird, and GeoEye1 have increased pixel resolution down to less than one meter for panchromatic images and 2-4 meters for multispectral images capturing the blue, green, red and NIR spectral regions (Table 1). The analysis of this imagery has provided a way to study large areas by allowing visualization of entire landscapes and regions and identification of individual tree species. Due to high temporal frequency of flights over the same area (3 to 4 days), fine resolution satellites have facilitated assessments of forest structure, condition and health across multiple spatial and temporal scales. Imagery from these satellites has improved the identification and mapping of individual forest species across entire landscapes. While the high spatial resolution allows for delineation of single tree crowns, the multispectral bands allow for determination of variations of canopy greenness within forest stands (Guo et al., 2007). In particular, these satellites have been successfully applied for forest inventory in tropical environments and allowed for the mapping of tree crown sizes (Martinez Morales et al., 2008), tree density, species identification, and assessment of temporal changes in individual tree growth and mortality (Clark et al., 2004; Martinez Morales et al., 2011).

Satellite	Multispectral	Pancromatic
Ikonos	4	1
QuickBird	2.62	0.65
WorldView2	2	0.65
GeoEye1	2	0.5

Table 1. Pixel resolution in meters for common fine resolution satellites.

While high spatial resolution satellite sensors can be used to assess forest structural characteristics, they only collect data on a limited number of spectral bands (blue, green, red, and near-infrared). Hyperspectral remote sensing, or imaging spectroscopy, collects data on hundreds of bands from visible to infrared wavelengths (0.4 to 2.5 μm). Due to higher definition of unique spectral signatures among vegetation types, this kind of data has expanded the potential to identify forest species and assess canopy biochemical and physiological properties such as leaf pigments, carbon and nitrogen content at the species level (Asner et al., 2005; Clark et al., 2005; Pu et al., 2008; Féret and Asner, 2011). Imagery from Hyperion EO-1, a hyperspectral satellite which detects 220 spectral regions at 30-m pixel resolution (eo1.usgs.gov), has been used to map structural vegetation metrics and indices of forest productivity at regional scales (Pu and Gong, 2004; Asner et al., 2005). However, the spatial resolution of this satellite does not allow resolving forest stands and individual trees. The Airborne Visible and Infrared Imaging Spectrometer (AVIRIS) built by NASA (aviris.jpl.nasa.gov) provides 224 contiguous spectral bands with pixel resolution varying from 2 to 20-m depending on flight altitude. These data have improved remotely sensed predictions of forest health, biomass, species identity and variation through a better understanding of spectral responses of forest canopies at the species level (Roberts et al., 1997; Asner and Lobell, 2000). Asner et al., 2008 used AVIRIS data to analyze the reflectance properties of 37 distinct species (7 common native and 24 introduced tree species) in order to spectrally differentiate between native and alien trees in a montane forest in Hawaii. They found that the reflectance signatures of Hawaiian native trees were unique from those of introduced trees. Since the AVIRIS imaging system is costly and frequently unavailable, a number of companies such as Hughes, Lockheed and Surface Optics among others, have developed a variety of visible and infrared imaging spectrometers available in the market. Greg Asner's research team has pioneered the use of airborne hyperspectral sensors to extract detailed biochemical data on plant canopies in Hawaii's forests. Distinct structural or biochemical signatures have been used to map the distribution of native forest species and several tree and shrub invasive species (Asner et al., 2008a; Asner et al., 2008b).

Although passive satellite sensors offer routine and repeated assessments at scales down to 1 meter, this technology has difficulty in capturing reflectance beyond upper canopy layers and is better suited for mapping horizontal structure rather than vertical structure (Weishampel et al., 2000). Active remote sensing technologies offer great potential to spatially map a forest three-dimensional (3D) structure at various scales from landscape, stand and individual tree levels. Active satellite systems based on interferometric synthetic aperture radar (InSAR) can provide measures of horizontal and vertical structure of vegetation at regional scales (Treuhaft & Siqueira, 2000), but this technology does not provide the spatial resolution required in detailed forest studies. However, active airborne laser scanning sensors such as LIDAR (Light Detection and Ranging System) are providing improved capabilities for the estimation of forest canopy dimensions at the individual tree level (Weishampel et al., 2000; Hyde et al., 2005; Chen, 2006). Small foot-print LIDAR systems have provided 3D surveys of forest canopy and have resolved some of the challenges not met by existing techniques for measuring canopy structure (Hetzel et al., 2001; Tickle *et al*., 2006; Chen et al., 2006). The isolation and extraction of tree structural information from LIDAR imagery has allowed more explicit ecological modeling through the estimation of individual-tree height, crown area, trunk height, biomass and leaf area (Henning, 2005; Chen et al., 2007, Chen, 2010). Chen et al., 2006 isolated trees from small-footprint airborne LIDAR data in deciduous oak woodland in California using a marker-controlled watershed segmentation method and a canopy height model derived from the LIDAR data. In the same site, Chen et al., 2007 proposed a new metric called canopy geometric volume derived from LIDAR data to estimate individual tree height, crown size, LAI, basal area and stem volume at 70 % accuracy. On Hawaii montane forests, Asner et al., 2009 derived canopy vertical profiles from LIDAR imagery in order to quantify 3-D forest structure and above ground biomass (AGB). They found that LIDAR measurements were strong predictors of AGB ($R^2 = 0.78$) across sites and species. Combining or fusing the highly detailed vertical measurements provided by LIDAR and the broad-scale mapping capabilities of passive optical sensors can provide dramatic increases in forest mapping and characterization. Wulder et al., 2004 used texture metrics from Landsat images to improve LIDAR estimates of canopy height. Hyde et al. 2006, combined forest structural information from LIDAR and QuickBird to improve estimates of canopy height and biomass. Asner et al. (2008a) combined airborne LIDAR and hyperspectral imagery to differentiate and map native and alien tree species in Hawaii montane forests, including understory plants like Kahili ginger (*Hedychium gardnerianum*) and strawberry guava. Therefore, airborne systems combining LIDAR with hyperspectral sensors have the highest potential for reliable estimations of individual-tree structure parameters such as canopy size, volume and leaf area.

However, airborne LIDAR imaging systems have disadvantages due to the high cost of flight time and a large number of flights for imaging entire landscapes. Resource Mapping Hawaii Inc (www.remaphawaii.com), developed a system for mapping detailed forest structural and morphological characteristics using ultra high resolution airborne multispectral imagery at 1.5 cm per pixel. The Nature Conservancy of Hawaii is employing such imaging system to map the distribution of Australian tree fern. Geo-referenced locations of individual trees can be obtained from this imagery and uploaded to a handheld GPS, allowing for more efficient eradication efforts (Ambagis et al., 2009). This imaging technology best complements to field inventories, providing detailed information of vegetation in areas that are remote, inaccessible, or rapidly changing.

3. Remote sensing applications in forest research

With the development of advanced image processing techniques, remote sensing technology has rapidly expanded to allow estimation of forest cover in heterogeneous landscapes and estimation of tree density, species identification and assessment of temporal changes in individual tree growth, health and mortality across entire landscapes (Carleer and Wolff, 2004; Carleer and Wolff, 2005; Clark et al., 2004; Chubey et al., 2006; Soudani et al., 2006). Martinez Morales et al., 2011 developed practical methodologies to analyze fine resolution satellite imagery using pixel-based image classification techniques for forest resource assessment. They fused GeoEye1 multispectral and panchromatic bands to conduct landscape-level assessments of koa (*Acacia koa*) forest health across an elevation range of 600–1,000 m asl in the island of Kauai. The goal of the study was to assess the spatial distribution of koa forest dieback patterns across a gradient of temperature and rainfall in order to determine the influence of these environmental factors on dieback patterns. The spectral bands were analyzed using a supervised classification technique to differentiate and classify pixels representing healthy and unhealthy koa stands and other land cover classes existing in the landscape. They classified healthy koa forest stands at 87 % accuracy from areas dominated by introduced tree species and differentiated healthy koa stands from those exhibiting dieback symptoms at 98 % accuracy. A landscape-scale map of healthy koa forest and dieback distribution (Fig. 1) demonstrated larger presence of unhealthy koa stands in areas with lower elevation and precipitation and higher temperature.

While pixel-based image classification involves assigning individual pixels to a vegetation class according to unique reflectance patterns across the spectral bands (spectral signature), object-based methods also include class shape and texture as additional parameters (Jensen 2000). Object-based analysis and image segmentation techniques have been increasingly applied in fine resolution multispectral imagery as an alternative to overcome the difficulties of conventional procedures of spectral image analysis for various forestry applications (Chubey et al., 2006; Herold et al., 2003; Hu et al., 2005). Instead of analyzing a single pixel spectral response, a wide range of spectral values in a group of pixels representing a forest stand is interpreted as a homogeneous object which can be further segmented into even more homogeneous subgroups. Pixel grouping can be controlled by the user through the definition of parameters such as size, homogeneity and shape in order to reduce heterogeneity in the resulting objects (Chubey et al., 2006). Wang et al. (2004) utilized a combination of spectral classification techniques and segmentation methods for tree-top detection and tree classification in a forested area in British Columbia, Canada. They calculated the first principal component from a set of spectral images from the Compact Airborne Spectrographic Imager and applied a Laplacian edge detection method for tree-crown delimitation. They further applied a segmentation technique and tree-top markers in order to differentiate final individual tree crowns at 85% accuracy. In a Belgian forest, Kayitakire et al. (2006) found highly significant relationships between image texture metrics extracted from the IKONOS panchromatic band with several forest productivity indices including tree density, height, crown size and basal area. Since the IKONOS NIR band contains important vegetation information, Herold et al. (2003) used this band to derive various texture and landscape metrics that classified forests at 78 % accuracy along a California coast region. Martinez Morales et al. (2008) analyzed fused Ikonos multispectral and panchromatic bands with spectral and object-based classification methods, to estimate forest cover at 86% accuracy in a Hawaiian dry forest ecosystem. Their comparison between spectral and object-based methods demonstrated superior performance of object-based classification algorithms in delineating tree canopy cover in a highly heterogeneous dry forest environment. The object-based approach allowed for differentiation of tree crowns, tree shades, and their transitional areas from other objects of similar size, shape, or spectral range such as green grass and lava outcrops (Fig. 2). A particular important result was the clear delimitation of individual tree crown areas that can be useful for forest inventory even on high spatial heterogeneity of vegetation conditions.

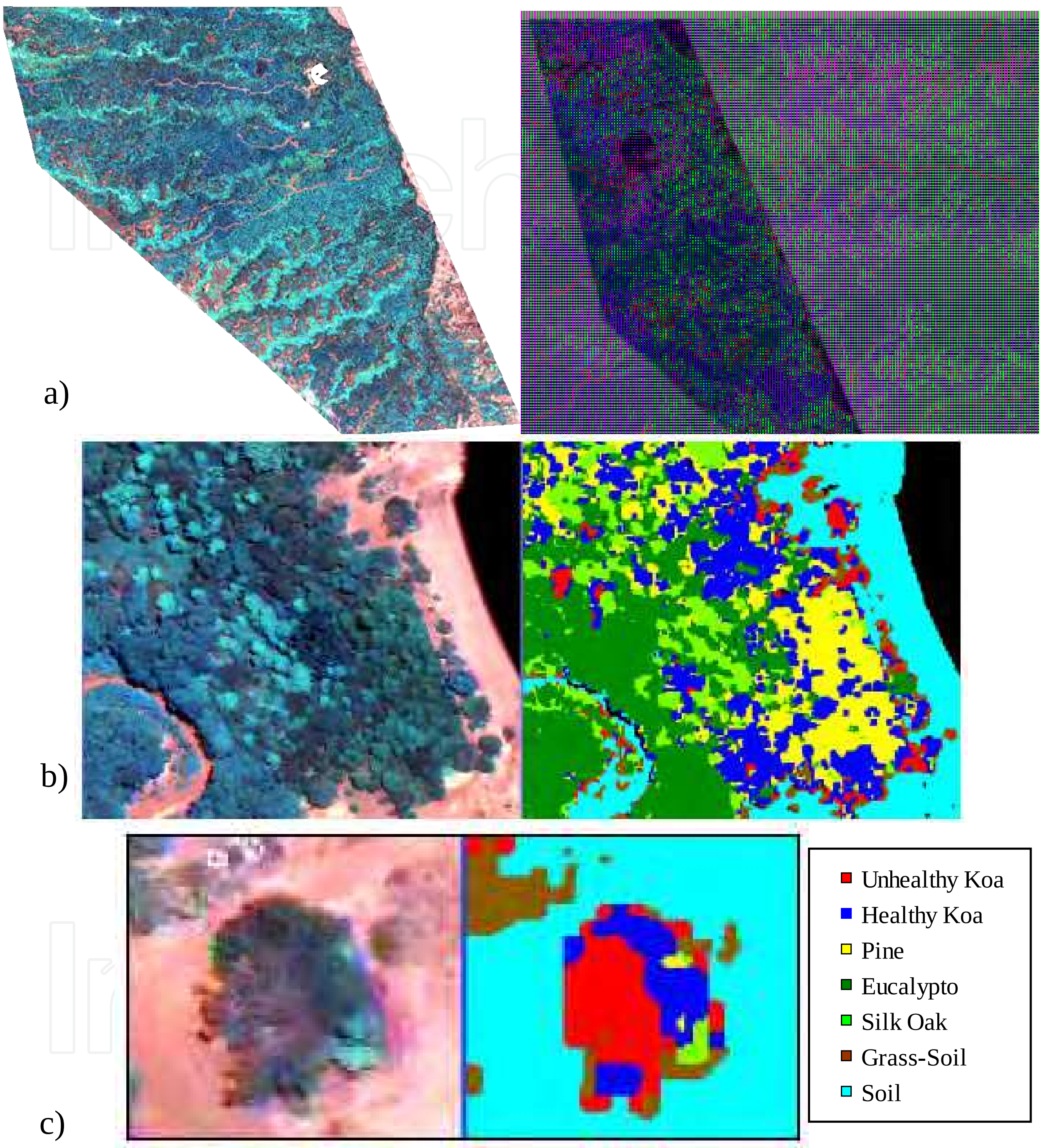

Fig. 1. A montane forest ecosystem from the Island of Kauai as viewed by the GeoEye1 satellite. a) Natural color composite at 0.5-m pixel resolution (left) and its corresponding classification (right); b) Image close-up depicting clear differentiation among tree species; c) Detailed close-up showing classification of diseased from healthy forest stands (Martinez Morales et al., 2011).

a)

b)

c)

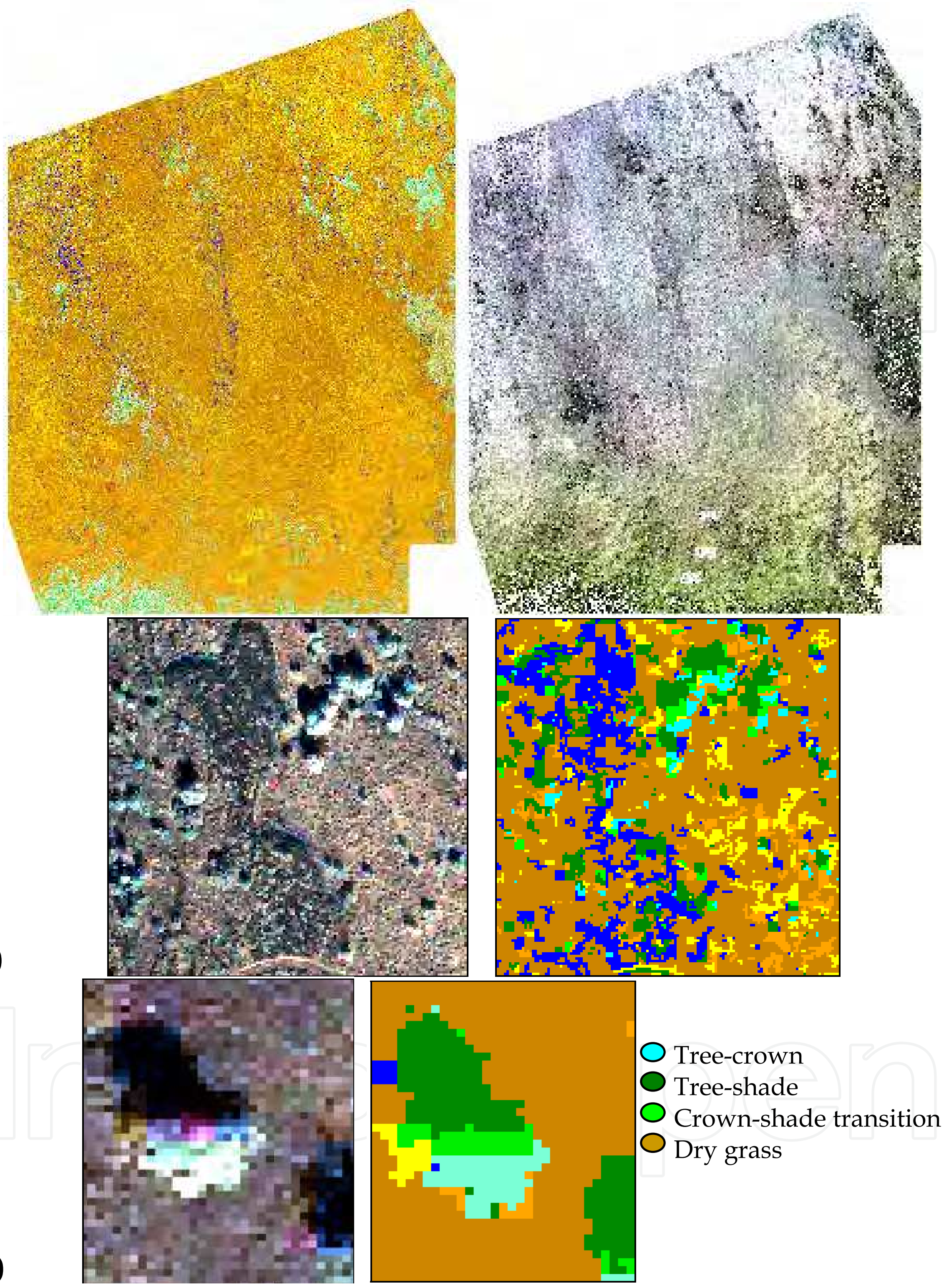

Fig. 2. A dry forest ecosystem from the north Kona region in the Island of Hawaii as viewed by the Ikonos-2 satellite. a) Natural color composite at 1-m pixel resolution (left) and its corresponding classification (right); b) Image close-up depicting differentiation among objects with similar reflectance (tree crowns from shrubs and grasses and tree shades from lava outcrops); c) Detailed close-up showing clear delineation of individual tree crowns and tree shades (Martinez Morales et al., 2008).

Since the reflectance of green vegetation is low in the red region due to chlorophyll absorption, and strong in the NIR due to internal leaf structure, a number of vegetation indices (VIs) (Table 2) have been calculated using these two regions of the reflectance spectrum for assessments of vegetation biomass, chlorophyll abundance and light absorption (Baugh and Groeneveld 2006), phenological changes in forested areas (Loveland et al., 2005) and for detailed identification of forest tree species (Soudani et al. 2006, Martinez Morales et al., 2012). Roberts et al. (1997) successfully used the Normalized Difference Vegetation Index (NDVI) from AVIRIS hyperspectral imagery to estimate LAI and canopy cover at moderate scales in a California forest. Carleer and Wolff (2004) derived NDVI, principal components (PCs) and texture metrics from Ikonos satellite data and used them in the identification of tree species in a forested area in Belgium. Seven tree species, including two different ages, were successfully identified with 86% overall classification accuracy. At various forest stands of tenths of hectares, Soudani et al. (2006) used five different VIs, such

Vegetation index	Formulae Source
1. Simple Ratio	SR = NIR / R (Jordan 1969)
2. Normalized Difference Vegetation Index	NDVI = NIR - R / NIR + R (Rouse et al. 1973)
3. Soil Adjusted Vegetation Index	SAVI = (1 + L) * (NIR - R) / (NIR + R + L) L = 0.5 (canopy background adjustment factor) (Huete 1988)
4. Atmospherically Resistant Vegetation Index	ARVI = (NIR - R) / (NIR + Q_{RB}), Q_{RB} = R - γ (B - R), γ = 1 (calibration factor) (Kaufman and Tanré 1992)
5. Modified Soil Adjusted Vegetation Index	MSAVI = (1 + L) * (NIR - R) / (NIR + R + L) L = 1 - 2a * NDVI * WDVI (Qi et al. 1994)
6. Enhanced Vegetation Index	EVI = G * (NIR - R) / (NIR + C1*R - C2*B + L) with G = 2.5, C1 = 6, C2 = 7.5, L = 1 (Liu and Huete 1995)
7. Modified Simple Ratio	MR = (NIR / R - 1) / ((NIR / R)$^{1/2}$+1) (Chen 1996)

Table 2. Spectral vegetation indices. R, NIR and B are red, near-infrared, and blue bands, respectively. For Modified Soil Adjusted Vegetation Index, WDVI = NIR - aR (a = 0.08, slope of the soil line). For Enhanced Vegetation Index, G, C1, C2 and L are coefficients to correct for aerosol scattering, absorption, and background brightness.

as NDVI, Soil Adjusted Vegetation Index (SAVI), Atmospherically Resistant Vegetation Index (ARVI), Enhanced Vegetation Index (EVI) and Simple Ratio (SR) calculated using data from the IKONOS and SPOT satellites to accurately classify various forest stands in France. They found that ARVI, NDVI and SR had similar and better predictions of LAI compared to SAVI and EVI. Kayitakire et al. (2006), estimated forest productivity at regional and landscape scales by relating VIs with LAI. This relationship has been used as a strong diagnostic tool to make silvicultural management recommendations (Flores 2006). Flores (2006) developed empirical models that were not affected by site, stand structure or time of the year to estimate LAI in broad areas of southern loblolly pine stands in USA using NDVI and SR from Landsat data and airborne hyperspectral data. Asner et al., 2005 found that the canopy water content index (NDWI) calculated from EO-1 data was superior than NDVI in capturing climate driven variations in canopy structure of a Hawaiian forest. In a Hawaiian koa forest, Martinez Morales et al., 2012 used Ikonos multispectral imagery to calculate six VIs (ARVI, EVI, NDVI, SAVI, SR, Modified Soil Adjusted Vegetation Index (MSAVI) and Modified Simple Ratio (MSR)) as a measure of vegetation greenness, and related those to biophysical measures of forest productivity such as tree height, basal area, leaf area index and foliar nutrients for spatial prediction at the landscape scale. This procedure allowed a clear differentiation of koa stands from areas dominated by grasses, shrubs, and bare lava. Vegetation indices allowed differentiation of three koa forest stand classes at upper, intermediate and lower elevations. In agreement with the image classification, analysis of variance of tree height and leaf phosphorus suggested there were also three significantly different groups of koa stands at those elevations.

4. Conclusions

Fine spatial resolution remote sensing allows not only visual interpretations of forest species but also automated classification of forest stands. Since the electromagnetic radiation captured by satellites has interacted with forest canopies through chemical absorption or physical scattering, it contains information about the chemical and physical properties of each vegetation type in the landscape. Therefore, the analysis of spectral data allows distinguishing not only forests species but also forest structural variations based on their unique reflection properties across the electromagnetic spectrum. Based on canopy greenness, analysis of these imagery can also be used to differentiate diseased from healthy forest stands. Such applications should improve forest inventory and collection of forest attributes for productivity assessments among forest scientists, decision-makers, and the general public involved in the ecological restoration, conservation and silviculture of important tree species worldwide.

Although field measurements for forest resource inventory and assessment are more accurate than satellite measurements, satellites collect data across broad areas, sample the full range of variation in forest metrics, capture broad trends and dynamic change in forest stands and help expand our understanding of forests beyond the plot level. As such, satellite data allow for integration across ground measurements, extending them across landscapes and regions and allowing detection of spatial and temporal changes in forests that we could not measure using conventional survey methods. Therefore, the analysis of satellite imagery has become a practical necessity to measure and manage forests at landscape and regional scales. The greatest strengths of satellite imagery are their monthly to daily frequency and view of entire regions, which could improve monitoring and verification of forest management for sustainable harvest and carbon sequestration. Aerial photos have proven useful, but the technology is costly and limited to small areas. The advent of high spatial resolution satellites such as Ikonos, Quickbird and GeoEye1 has changed the cost and availability of high-resolution imagery. If available for an area, archived imagery from these satellites can be acquired for one third of the original cost. With current technology, fine resolution remote sensing is suited to differentiate among forest species with classification accuracy usually decreasing with an increasing number of forest classes. It is also difficult to distinguish forests of different ages or composition, and primary forests from tree plantations and older secondary forests. However, remote sensing is rapidly developing by technological advancements in data gathering and processing. The GeoEye2 satellite at 0.25 m pixel resolution will be launched in 2012 and it is expected to revolutionize the management of forest ecosystems worldwide since it will allow more accurate assessment of the small-scale forest variability across environmental gradients. Improved characterizations and delimitations of forest species, stands types and growth stages along environmental gradients will allow development of more efficient silvicultural management practices according to site-specific ecological requirements.

The integrated analysis of environmental data with remote sensing imagery in a Geographical Information System (GIS) framework, allows inferences on how environmental factors influence forest ecosystem functioning. The increasing integration of GIS and remote sensing has facilitated display and communication of satellite imagery between scientists and the general public, as witnessed by the explosive growth in mapping using tools like Google Earth. Overall, remote sensing technologies are proving to be powerful research and management tools for the inventory and assessment of forests around the world. We are now at the point where both satellite and airborne sensing systems can provide reliable and detailed information at the individual-tree level. These technologies will become increasingly important for assessment and management of forests worldwide as we continue to face the challenges of land use pressures, invasive species, and climate change.

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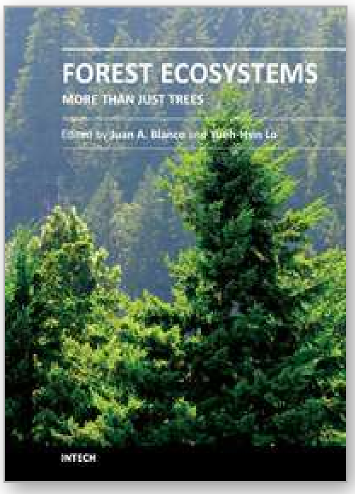

Forest Ecosystems - More than Just Trees
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The common idea for many people is that forests are just a collection of trees. However, they are much more than that. They are a complex, functional system of interacting and often interdependent biological, physical, and chemical components, the biological part of which has evolved to perpetuate itself. This complexity produces combinations of climate, soils, trees and plant species unique to each site, resulting in hundreds of different forest types around the world. Logically, trees are an important component for the research in forest ecosystems, but the wide variety of other life forms and abiotic components in most forests means that other elements, such as wildlife or soil nutrients, should also be the focal point in ecological studies and management plans to be carried out in forest ecosystems. In this book, the readers can find the latest research related to forest ecosystems but with a different twist. The research described here is not just on trees and is focused on the other components, structures and functions that are usually overshadowed by the focus on trees, but are equally important to maintain the diversity, function and services provided by forests. The first section of this book explores the structure and biodiversity of forest ecosystems, whereas the second section reviews the research done on ecosystem structure and functioning. The third and last section explores the issues related to forest management as an ecosystem-level activity, all of them from the perspective of the �other� parts of a forest.