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Satellite remote sensing of mangrove forests: Recent advances and future opportunities

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Abstract

Mangroves are salt tolerant woody plants that form highly productive intertidal ecosystems in tropical and subtropical regions. Despite the established importance of mangroves to the coastal environment, including fisheries, deforestation continues to be a major threat due to pressures for wood and forest products, land conversion to aquaculture, and coastal urban development. Over the past 15 years, remote sensing has played a crucial role in mapping and understanding changes in the areal extent and spatial pattern of mangrove forests related to natural disasters and anthropogenic forces. This paper reviews recent advancements in remote-sensed data and techniques and describes future opportunities for integration or fusion of these data and techniques for large-scale monitoring in mangroves as a consequence of anthropogenic and climatic forces. While traditional pixel-based classification of Landsat, SPOT, and ASTER imagery has been widely applied for mapping mangrove forest, more recent types of imagery such as very high resolution (VHR), Polarmetric Synthetic Aperture Radar (PolSAR), hyperspectral, and LiDAR systems and the development of techniques such as Object Based Image Analysis (OBIA), spatial image analysis (e.g. image texture), Synthetic Aperture Radar Interferometry (InSAR), and machine-learning algorithms have demonstrated the potential for reliable and detailed characterization of mangrove forests including species, leaf area, canopy height, and stand biomass. Future opportunities include the application of existing sensors such as the hyperspectral HYPERION, the application of existing methods from terrestrial forest remote sensing, investigation of new sensors such as ALOS PRISM and PALSAR, and overcoming challenges to the global monitoring of mangrove forests such as wide-scale data availability, robust and consistent methods, and capacity-building with scientists and organizations in developing countries.

Keywords

canopy structure, hyperspectral, image texture, leaf area index, mangrove, OBIA, remote sensing, SAR

I Introduction

Mangrove forests and shrubland, or mangroves, form important intertidal ecosystems that link terrestrial and marine systems and provide valuable ecosystem goods and services (Alongi, 2002). For example, mangroves are a foundation assemblage of trees that provide habitat for numerous terrestrial and marine species including economically and ecologically important fisheries (Nagelkerken et al., 2008). Despite the economic and ecological value of

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mangroves to the coastal environment including fisheries, more than 25% of global mangrove area was cleared between 1980 and 2000 (Wilkie and Fortuna, 2003). Detailed and accurate characterizations of mangroves are important to support ecological understanding and management of mangroves. Remote sensing has had a crucial role in monitoring mangroves, but the vast majority of the applications have been used to map areal extent and patterns of change at local scales. Recent advances in data and techniques have not only demonstrated the potential for improved accuracy of land cover classification and change-detection, but the capacity to characterize stand characteristics such as leaf area, canopy closure, species composition, canopy height, and standing biomass. This paper describes the following: (1) the traditional approaches of mapping mangrove areal extent and change using remote sensing; (2) recent advancements in remotely sensed data and analysis techniques for characterizing mangroves in terms of leaf area, species composition, and standing biomass; and (3) future opportunities for integration of these recent advancements and wide-scale application to provide regional and global monitoring of mangroves and indicators of ecological goods and services in the context of continued and growing threats from deforestation, natural disasters, and global climate change, especially sea-level rise.

II Mangrove vegetation and ecosystems

Mangroves are an assemblage of woody halophytes (i.e. salt tolerant plants) that are the foundational species of intertidal forest and shrubland ecosystems that occur along tropical and subtropical coastlines, estuaries, lagoons, and river deltas (Hogarth, 2007; Smith, 1992; Tomlinson, 1986). While mangrove composition is often characterized by a strong zonation in community composition, based primarily on soil salinity related to tidal inundation (Tomlinson, 1986), other geomorphic, edaphic, climatic, and biotic factors can create more complex patterns (Duke et al., 1998; Ellison, 2002; Ewel et al., 1998; Farnsworth, 1998; Lee, 1999; Onuf et al., 1977).

As Tomlinson (1986) describes, mangroves tend to have biological characteristics associated with pioneer terrestrial trees such as large numbers of propagules, wide dispersal, fast growth rates, light as a limiting resource, uniform crown shape, and a prolonged flowering period. Mangrove communities also have many pioneer characteristics such as low species richness, low stratification, and few climbers or epiphytes. However, mangrove trees and communities have some characteristics of mature forests as well, such as a long life span, low leaf palatability, medium leaf size, hard wood, and the absence of undergrowth. Mangroves demonstrate a negative scaling relationship between mean stem diameter and stem density, typical of the self-thinning theory of mono-specific stands as well as asymptotic standing biomass accumulation typical of upland tree communities (Ward et al., 2006). Furthermore, mangrove trees have strong allometric relationships between stem diameter, tree height, and aboveground biomass (Fromard et al., 1998; Smith and Whelan, 2006). Thus, mangrove forests tend to form distinguishable patterns of community composition and predictable canopy structure.

The ecosystem goods and services that mangroves provide include carbon sequestration, the support of biodiversity through structure, nutrients and primary productivity, filtration of pollutants, and the potential to reduce the impacts of hurricanes and tsunamis (Alongi, 2002). Primary productivity of mangroves can rival terrestrial, tropical rainforests (Alongi, 2002). Even though most productivity in mangroves is attributed to mangrove trees or bacteria in the soils, roughly 9% and 30% of carbon is consumed through herbivory or exported to the nearshore, respectively (Duarte and Cebrian, 1996). Mangroves provide protection from predators

Table 1. Traditional remote sensing systems and mangrove forest studies

Sensor(s)	Studies
Aerial photography	Benfield et al. (2005); Chauvaud et al. (1998); Dahdouh-Guebas et al. (2006); Eslami-Andargoli et al. (2009); Everitt et al. (2007); Fromard et al. (2004); Hossain et al. (2009); Jones et al. (2004); Krause et al. (2004); Manson et al. (2001); Murray et al. (2003)
Landsat MSS, TM, or ETM+	Beland et al. (2006); Cornejo et al. (2005); Giri et al. (2008);Green et al. (1998); James et al. (2007); Krause et al. (2004); Lee and Yeh (2009); Liu et al. (2008); Long and Skewes (1996); Manson et al. (2001); Mumby et al. (1999); Paling et al. (2008), Ruiz-Luna and Berlanga-Robles (2003); Vasconcelos et al. (2002)
SPOT HVR, HRVIR, or HRG	Chauvaud et al. (2001); Gao (1998, 1999); Green et al. (1998); Lee and Yeh (2009); Mumby et al. (1999); Rasolofoharinoro et al. (1998); Saito et al. (2003)
ASTER	Al Habshi et al. (2007); Vaiphasa et al. (2006)
IRS C or D	Mantri and Mishra (2006); Pattanaik et al. (2008); Ramachandran et al. (1998); Reddy and Pattanaik (2007)

and increased food availability for marine fauna (Laegdsgaard and Johnson, 2001) and they have been linked to increased fish biomass (Mumby et al., 2004) as well as overall fish populations (Nagelkerken et al., 2008). Furthermore, many other marine species rely directly or indirectly on litter fall for food. These ecosystem goods and services are estimated to be worth about US $10,000 per hectare per year or about US $180 billion globally (Costanza et al., 1997).

Major threats to mangroves include logging for fuel and timber, land conversion to aquaculture, primarily shrimp ponds, coastal development for shipping, and the direct and indirect effects of urban development including fresh water diversions (Gopal and Chauhan, 2006). The value of mangroves has been recognized by many governmental and non-governmental organizations (Wilkie and Fortuna, 2003). Efforts to manage mangroves require wide-scale monitoring to track changes in areal extent, health, and ecological functioning. Remote sensing plays a crucial role in the monitoring of mangroves to track deforestation (e.g. Giri et al., 2007; Lee and Yeh, 2009; Manson et al., 2001; Mantri and Mishra, 2006; Paling et al., 2008; Thu and Populus, 2007), the impact of natural disasters such as hurricanes (Doyle et al., 2009; Erftemeijer, 2002) and tsunamis (Giri et al., 2008; Olwig et al., 2007; Sirikulchayanon et al., 2008), reforestation projects (Al Habshi et al., 2007; Beland et al., 2006) and natural coastal dynamics (Fromard et al., 2004).

III Traditional approaches to mangrove remote sensing

Aerial photography (AP) and legacy high resolution systems such as Landsat and SPOT are by far the most common approaches to mangrove remote sensing (Newton et al., 2009). AP has been widely used in the mapping and assessment of mangroves (see Table 1). AP can be more cost effective over small areas than satellite remote sensing (Mumby et al., 1999) and can provide fine grain imagery unavailable from satellite remote sensing due to government restrictions. Furthermore, historical imagery allows for change-detection well before the availability of satellite remote sensing. AP is more accessible to developing nations in which the majority of the world's mangroves grow and AP can provide very rapid assessments for monitoring change (Dahdouh-Guebas et al., 2006) in times of crisis. Most studies have used visual interpretation of AP to map the extent of mangrove and detect

Table 2. Traditional remote sensing techniques and mangrove forest studies

Technique	Studies
Visual interpretation	Benfield et al. (2005); Dahdouh-Guebas et al. (2006); Fromard et al. (2004); Murray et al. (2003)
Classification of digital AP	Chauvaud et al. (1998); Everitt et al. (2007); Krause et al. (2004)
Unsupervised classification	Bhatt et al. (2009); Green et al. (1998); James et al. (2007); Murray et al. (2003)
Supervised classification	Al Habshi et al. (2007); Chauvaud et al. (2001); Cornejo et al. (2005); Gao (1999); Giri et al. (2007); Green et al. (1998); Lee and Yeh (2009); Ruiz-Luna and Berlanga-Robles (2003); Saito et al. (2003); Thu and Populus (2007)
Hybrid classification	Giri et al. (2008); Hossain et al. (2009); Paling et al. (2008)
Spectral transformation	Green et al. (1998); Krause et al. (2004); Manson et al. (2001); Mantri and Mishra (2006); Paling et al. (2008)
Spectral vegetation indices	Krause et al. (2004); Lee and Yeh (2009); Mantri and Mishra (2006); Rasolofoharinoro et al. (1998); Thu and Populus (2007)

change between images, although digital AP now allows for computational classification (see Table 2). Dahdouh-Guebas et al. (2006) demonstrated that fine grain AP can be successfully used to detect and map individual species. Major limitations to AP are the limited areal extent and relatively high costs of data acquisition over large geographic areas as well as the possible inconsistencies inherent in AP data such as uneven brightness and parallax distortion. Satellite-based remote sensing is essential for cost effective and repeatable mapping and monitoring of mangroves across geographic scales.

The vast majority of mangrove remote sensing studies (see Table 1) have employed high resolution satellite imagery (i.e. spatial resolution between 5 and 100 m) such as Landsat (MSS, TM, or ETM+), SPOT (HVR, HRVIR, or HRG), ASTER, or IRS (1C or 1D). Table 3 provides further details on these sensor systems. The techniques used to detect and delineate mangrove have primarily involved unsupervised classification techniques such as the ISODATA approach, supervised classification techniques such as the maximum likelihood classification (MLC), mahalanobis distance, or other techniques commonly available in commercial image processing software, or a hybrid unsupervised/supervised classification scheme (see Table 2 for a list of studies). Other common approaches for the classification of mangroves using multispectral imagery include preprocessing steps such as spectral transformations such as principal components analysis (PCA) or Tassel-Cap Transformation (Crist and Cicone, 1984), or spectral vegetation indices such as Normalized Difference Vegetation Index (NDVI) or Simple Ratio (SR). In a comparison of classification techniques and data types, Green et al. (1998) found that the classification of PCA data performed significantly better than classifications using raw satellite bands. Additionally, the authors reported that the difference in classification accuracy using either Landsat or high resolution airborne imagery was small.

Using traditional data and techniques, reported classification accuracies of mangroves classes ranged from 75% to 90% for producer's and user's accuracies, though many applied studies omit detailed accuracy assessments. The omission of accuracy assessments is likely due to disconnect between the remote sensing and other disciplines (e.g. Newton et al., 2009). Accuracies tend to be higher for classifications using contemporary imagery with ground data than classifications using spectral library for

Table 3. Passive optical satellite remote sensing systems (B = blue; G = green; R = red; NIR = near-infrared; SWIR = shortwave infrared; V = visible)

Sensor/system	Platform	No. of band(s)	Spectral range	Spatial resolution	
				MSS	Pan.
High resolution sensors					
MSS (Multi Spectral Sensor)	Landsat 1, 2, 3	4	B,G,R,NIR	~80 m	
TM (Thematic Mapper)	Landsat 4, 5	6	B,G,R,NIR,SWIR	30 m	
ETM+ (Enhanced Thematic Mapper Plus)	Landsat 7	6	VNIR,SWIR	30 m	15 m
HVR (High Resolution Visibility)	SPOT (Satellite Pour l'Observation de la Terre) 1, 2, 3	3	G,R,NIR	20 m	10 m
HRVIR (High Resolution Visible and Infrared)	SPOT (Satellite Pour l'Observation de la Terre) 4	4	G,R,NIR,SWIR	20 m	10 m
HRG (High Resolution Geometrical)	SPOT (Satellite Pour l'Observation de la Terre) 5	4	G,R,NIR,SWIR	10 m (VNIR); 20 m (SWIR)	2.5
ASTER*	Terra	10	G,R,NIR; 6-SWIR	15m (VNIR); 30 m (SWIR)	
IRS (Indian Remote-Sensing Satellite) 1C, 1D		4	G,R,NIR,SWIR	23 m	5.8 m
ALI (Advanced Land Imager)	EO-1 (Earth Observing)	9	2-B,G,R,2-NIR,2-SWIR	30 m	15 m
Very high resolution sensors					
Quickbird		4	VNIR; Pan	2.4 m	0.6 m
IKONOS		4	VNIR; Pan	4 m	1 m
PRISM**	ALOS (Advanced Land Observation System)	1	Pan	N/A	2.5 m
WorldView-2		8	VNIR; Pan	<2 m***	<0.5 m***
GeoEye-1		4	VNIR; Pan	1.65 m	0.41 m
Other optical sensors					
GLAS (Geoscience Laser Altimeter System)	IceSAT (Ice, cloud and land elevation Satellite)	LiDAR, 2	Green (532 nm), NIR(1064 nm)	70 m footprint; 170 m spacing	
HYPERION	EO-1 (Earth Observing)	Hyper-spectral: 220	400–2500nm	30 m	

*Advanced Spaceborne Thermal Emission and Reflectance Radiometer
**Panchromatic Remote-sensing Instrument for Stereo Mapping
***Maximum resolution limited by US government

Table 4. Synthetic Aperture Radar (SAR) remote sensing systems. Polarization indicated by transmit and receive polarizations, respectively (H = horizontal polarization; V = vertical polarization).

Sensor	Platform	Band(s)	Polarization(s)	Spatial resolution
SIR-C (Space-borne Imaging Radar)	Space Shuttle	C, L, X	HH,VH, VV	10–200 m
ERS-1 (European Remote-Sensing Satellite)	European Remote-Sensing Satellite	C	VV	25–100 m
JERS-1 (Japanese Earth Resource Satellite)	Japanese Earth Resource Satellite	L	HH	25–100 m
Radarsat-1		C	HH	8–100 m
Radarsat-2		C	HH,HV,VH, VV	3–100 m
ASAR (Advanced Synthetic Aperture Radar)	ENVISAT	C	HH, VH, HV, VV	25–150 m
PALSAR (Phased Array type L-band Synthetic Aperture Radar)	ALOS (Advanced Land Observation System)	L	HH, HV, VH, VV	10–100 m

land cover types with historical imagery (Giri et al., 2007). Despite the wide application of these traditional remote sensing data and techniques, there remain several limitations and challenges to traditional approaches to mangrove remote sensing. Confusion between mangroves and other vegetation is a commonly reported source of classification error (Al Habshi et al., 2007; Benfield et al., 2005; Gao, 1998). Another source of classification error is the omission of fringe mangroves that are less than the pixel size, resulting in mixed pixels (Manson et al., 2001). While the discrimination of mangrove density is possible with high resolution multispectral imagery (e.g. Green et al., 1998; Al Habshi et al., 2007), detection of individual species or estimation of canopy structure remain a challenge. For example, Ramsey and Jensen (1996) found no significant relationship between the spectral responses of different mangrove species using spectral bands available from Landsat. While estimation of canopy structure may be possible with high resolution imagery (Li et al., 2007), there are a number of challenges including mixed pixels (Green et al., 1997) and spectral saturation effects at higher biomass levels (Li et al., 2007) that limit the potential accuracy of these data. Furthermore, reliance on a single grain of analysis can skew detection, analysis, and interpretation of landscape patterns and change (Wang et al., 2009).

IV Recent advances

Traditional remote sensing approaches can provide important information for monitoring the areal extent and change of mangroves. New satellite sensors and techniques can potentially improve the accuracy of mangrove classifications, detect individual species, and provide reliable estimates of structure such as leaf area, canopy height, and biomass. There has been very rapid development of new remote sensing sensors and systems in recent years (e.g. Gillespie et al., 2008; Wooster, 2007). The new types of satellite sensors include very high resolution (VHR) systems (e.g. Quickbird, IKONOS, GeoEye-1 Worldview-2, and ALOS PRISM), Synthetic Aperture Radar systems (e.g. ALOS PALSAR, ASAR ENVISAT, and the Radarsat satellites), and LiDAR systems such as IceSAT/GLAS (see Tables 3 and 4 for details). Airborne sensors have been used to demonstrate the potential for satellite-based sensors such as the hyperspectral Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), TOPSAR and AIRSAR (Polarmetric SAR), and various commercial wave-form LiDAR systems. Several new analysis techniques have been developed such as Object-Based Image Analysis (OBIA), and image texture metrics, such as lacunarity, use spatial information to improve image classification that can be applied to newer and traditional remote sensing imagery. Techniques such as genetic algorithms, spectral angular mapping, or neural networks have been developed and adapted to deal with new types of data (e.g. hyperspectral data or fusion of multiple types of data). The following sections will describe recent advances of data and techniques by remote sensing objective.

V Mapping extent and change

Traditionally, multispectral remote sensing has been relatively effective at mapping the areal extent of mangroves but is limited in terms of spatial resolution or spectral resolution of sensors, or the inability of optical sensors to penetrate cloud cover. Newer types of imagery can address these limitations. For example, VHR imagery such as Quickbird or IKONOS can reduce the number of mixed pixels, hyperspectral imagery such as HYPERION can potentially detect fine differences in spectral signatures, and SAR imagery from sensors such as Radarsat or ASAR ENVISAT can penetrate cloud cover. While VHR imagery has been used to map mangrove extent, this type of imagery has been used almost exclusively for mapping individual species and characterizing canopy structure (see sections VI and VII). The few studies that have used VHR to map mangrove extent have relied upon visual interpretation over small geographic areas as a form of accuracy assessment of classifications derived from less expensive and coarser resolution imagery applied over a larger area (Giri et al., 2007; Howari et al., 2009).

Hyperspectral imagery provides detailed fine spectral resolution data that can be used to detect subtle differences in spectral reflectance. To date, the only satellite-based hyperspectral sensor, HYPERION on the EO-1 platform, has not been applied to mangrove studies. However, two studies have used airborne hyperspectral imagery to map the extent of mono-specific mangrove stands. While both D'Iorio et al. (2007) and Yang et al. (2009) demonstrate that hyperspectral imagery can produce very high accuracy classifications, D'Iorio et al. (2007) found that the improvement in accuracy of supervised classifications to detect red mangrove (*Rhizophora mangle*) using NASA's AVIRIS sensor was insignificant compared to classifications of imagery from ASTER imagery or aerial photography. These limited results suggest that further studies are needed to determine the effectiveness of mapping multispecific mangroves using hyperspectral imagery compared to other types of imagery.

A common problem inherent to passive optical remote sensing, particularly in humid tropical regions, is cloud cover. Synthetic Aperture Radar (SAR) is an active form of remote sensing in which a microwave signal is directed towards an object and the strength (i.e. amplitude) of the reflected signal is measured. Signal strength is altered through transmittance and reflectance of different media based on thickness and dielectric properties of the media as well as the wavelength and polarization of the microwave beam. For example, SAR can penetrate cloud cover, but reflects off solid surfaces like soil or stems. For more complex media such as forest canopy, the relative amount of signal transmittance through the canopy versus signal scattering is a function of the signal wavelength. In general, longer wavelengths have high transmittance. Hence, the architecture of mangrove trees, local geomorphic conditions and the specifications of the SAR system are critical elements to this type of remote sensing. For a more detailed background of SAR remote sensing, see Henderson and Lewis (1998).

SAR imagery from SIR-C, JERS-1, ERS-1, and Radarsat-1 has been successfully used to delineate mangrove extent (Fromard et al., 2004; Lucas et al., 2007; Pasqualini et al., 1999; Simard et al., 2002). Pasqualini et al. (1999) examined the potential of C and L band Polarmetric SAR (PolSAR) using vertical (VV) and cross polarization (VH) from SIR-C and found that only the L-band with VH polarization could accurately discriminate between diffuse, dense, and recessive mangroves and other land cover types. Simard et al. (2002) used a decision tree classifier to map coastal land cover, including low and high mangroves, and compare the effectiveness of the JERS, ERS, and combined imagery. They found that the combined imagery improved overall accuracy by 18% to 84%, though the authors note considerable confusion between low mangrove and other flooded forest classes. Souza-Filho and Paradella (2003) were able to visually interpret mangrove extent and the relative stage of growth using Radarsat imagery. In a follow-up study, Souza-Filho and Paradella (2005) were not able to statistically differentiate between land cover types including mangrove, based solely on Radarsat backscatter.

In recent years, new techniques have been developed or adapted to improve the accuracy of mapping the extent of mangrove and detecting change over time using either a data fusion approach to integrate different types of data or an Object-Based Image Analysis (OBIA) approach. Data fusion techniques can improve classification accuracy by drawing upon different data sources to maximize the dimensionality of available information. While a few studies have used visual interpretation of fused data (e.g. Souza-Filho and Paradella, 2005), most studies use multiple data sources within a rule-based classification scheme. Rule-based classifications separate out individual or groups of classes based on user-defined rules rather than solely on the spectral distance relationships used in many unsupervised and supervised classification schemes. Rule-based classifications are often invoked using a decision-tree that refines the separation of classes with each level. For example, DEM data are used to distinguish mangrove vegetation from neighboring terrestrial vegetation (Fatoyinbo et al., 2008; Islam et al., 2008; Liu et al., 2008). Additionally, rule-based classifications can utilize spatial information such as distance surfaces to separate mangrove from terrestrial vegetation based on a distance from ocean rule (Gao et al., 2004; Liu et al., 2008) The results of a rule-based classification can substantially improve classification accuracy over traditional methods. Gao et al. (2004) report substantial improvement in the classification accuracy of stunted mangroves (from 46.7% to 83.3%) and lush mangroves (from 68.3% to 96.7%). It is important to note that differences in the spatial resolution of multiple data sets can be a major challenge to data fusion techniques, especially when using archived data. For example, Manson et al. (2001) found that the use of an archived DEM did not accurately represent the topography of intertidal areas at an appropriate scale for mangrove mapping.

OBIA is a classification technique that uses objects rather than just individual pixels for image analysis. Objects are contiguous pixels that are grouped based on image properties or GIS data through an image segmentation process. Objects can be created at different levels. For example, lower-level objects could represent individual tree crowns; mid-level objects could represent a group of tree crowns of the same species and age; and high-level objects could represent a mangrove forest patch (e.g. Krause et al., 2004). Few studies have used OBIA to map the areal extent and change of mangroves as this approach is more commonly applied to species mapping (see section VI).

In a study by Conchedda et al. (2008), an OBIA approach was examined for effectiveness of detecting mangrove extent as well as change-detection between two images. The OBIA classification yielded very high accuracy for classifying mangroves with a user's accuracy greater than 97%. However, the effectiveness of change-detection using an integrated OBIA approach, in which two images are segmented together then classified, was less than a traditional image-difference change-detection technique. The traditional approach had an overall accuracy of 79.2% compared to 66.0% for the integrated OBIA approach. Conchedda et al. (2008) note that the segmentation process balances the size and number of objects, and in the case of the multidate segmentation, the objects were not sufficiently small to separate varying degrees of change between images.

VI Species composition

Species composition is an important characteristic of mangroves. Mangrove individuals often exhibit strong zonation patterns based on biotic and abiotic factors, and they can serve as a good indicator of geomorphic and environmental change (Souza-Filho and Paradella, 2005). Furthermore, habitat selection by animal can be a function of mangrove species, in additional to other factors (e.g. Dvorak et al., 2004). To detect individual species, spectral (e.g. leaf physiology) or spatial characteristics (e.g. crown shape or canopy pattern) of individual species must be detectable via remote sensing. Traditional satellite-based remote sensing techniques and data have been unable to detect species with needed confidence, given spatial and/or spectral constraints. However, newer data and techniques have demonstrated a number of methods in which the mapping of mangrove species is possible including VHR and hyperspectral imagery. The Quickbird and IKONOS sensors are used almost exclusively where satellite-based VHR are used due to their long-mission life and substantial archived imagery. Although the spectral information available from Quickbird and IKONOS is limited to the blue, green, red and near-infrared bands that are similar to those of Landsat TM or ETM+, the very high spatial resolution (see Table 3) may reduce the number and effect of mixed pixels and provide sufficient detail for the analysis of image texture as a metric of canopy structure. In a comparison of Quickbird and IKONOS imagery, Wang et al. (2004b) found that the IKONOS panchromatic and multispectral data outperformed Quickbird data for texture analysis and MLC, respectively, although both sensors are useful for mapping species.

A variety of sophisticated classification techniques have been used with VHR imagery to detect and classify mangrove species, including fuzzy classifications (Neukermans et al., 2008), Neural Networks (Wang et al., 2004a, 2008), support machine vectors (Huang et al., 2009), post-classification data fusion (Vaiphasa et al., 2006) and OBIA (Krause et al., 2004; Myint et al., 2008; Wang et al., 2004a, 2004b). Results from the few studies above indicate that spectral-only information for classification of individual species is often insufficient. For example, Neukermans et al. (2008) report an overall accuracy of 72% based of the mapping of four mangrove species and the surrounding land cover using Quickbird multispectral imagery and a fuzzy classification scheme. Similarly, Wang et al. (2004b) report an overall classification accuracy of nearly 75% or less for three mangrove species using Quickbird or IKONOS imagery with a MLC technique. Moreover, the user's accuracy for some individual species was as low as 55%, further demonstrating the limitations of distinguishing between mangrove species using just spectral data.

Classification accuracy of species is greatly improved when spatial information, such as image texture, is used. Image texture is often measured using first- and second-order metrics, computed from the grey-level co-occurrence matrix within a given window, lag distance, and direction (Barber and Ledrew, 1991; Haralick et al., 1973; Kayitakire et al., 2006). Wang et al. (2004b) report that image texture enhances image classification in both Quickbird and IKONOS imagery. Similarly, Wang et al. (2004a) found in a comparison of MLC and OBIA nearest neighbor classification techniques that while the pixel-based classification had an overall accuracy higher than that of the OBIA method (i.e. 88.9% versus 80.4%), due to classification confusion of white mangroves in the OBIA method, a hybrid approach provided the highest accuracy. The hybrid approach had an overall accuracy of 74%, 92%, and 98% for red (*Rhizophora mangle*), black (*Avicennia germinans*), and white (*Laguncularia racemosa*) mangrove canopies, respectively. In a comparison of MLC and neural network classification techniques, Wang et al. (2008) also found that the inclusion of image texture information improved the accuracies for the MLC and neural network techniques. Using a different machine learning method (i.e. support machine vector), Huang et al. (2009) report classification accuracies greater than 90% for red, black, and white based on spectral and image texture data.

Another approach to measuring image texture is lacunarity. Lacunarity is a metric of the fractal dimensionality of the whole or subset of an image and can be used to describe the pattern of canopy crowns and gaps (Myint et al., 2008). Similar to other metrics of image texture, lacunarity can be calculated based on varying window sizes, lags, and directions. In as study by Myint et al. (2008) used lacunarity transformed images were used during for the image segmentation process of an OBIA classification of individual mangrove species. Results showed an overall accuracy greater than 90% compared to an overall accuracy of 62.8% using a traditional pixel-based spectral classification. To date, there has not been a study to investigate the use of lacunarity to classify mangrove species using pixel- or object-based methods.

In a data fusion approach, Vaiphasa et al. (2006) used known relationships between mangroves species and soil pH to improve post-classification accuracy with a typical Bayesian probability model and pH map. Despite an overall classification accuracy improvement (i.e. from 76% to 88%), classification accuracy of some species remained low (<70%), likely due to the relatively coarse spatial resolution of the ASTER imagery.

Although there have not been any studies that have used satellite-based hyperspectral remote sensing to detect and map mangrove species, lab experiments indicate that discrimination between multiple species is possible. Vaiphasa et al. (2005) were able to discriminate between 14 different species common to Thailand using the Jeffries-Matusita distance technique, although there was reported confusion among *Rhizophora* species. Vaiphasa et al. (2007) used a genetic algorithm to find just six hyperspectral channels that were able to distinguish between 16 mangrove species. While the laboratory studies demonstrate the potential for hyperspectral remote sensing of species, a number of real world challenges remain, such as mixed pixels (e.g. canopy gaps and shadows, and tidal water), atmospheric distortion and contamination, and variance in leaf reflectance due to biotic and environment conditions. Similarly, Wang and Sousa (2009) found using linear discrimination analysis that six hyperspectral channels could discriminate between three common species in the Americas with very high accuracy (i.e. kappa >0.9). However, the six channels reported by Wang and Sousa (2009) do not agree with those reported by Vaiphasa et al. (2007).

VII Leaf area and canopy closure

Leaf area and canopy closure are important biophysical parameters for assessing evapotranspiration, carbon cycling, habitat conditions, and forest health (e.g. Kercher and Chambers, 2001; Kovacs et al., 2008; Pasher et al., 2007). While the remote sensing of leaf area and canopy closure are major areas of research for terrestrial forests, relatively little research has been done on mangroves. In fact, all but one satellite-based mangrove leaf area remote sensing study has been conducted in the same estuary – the Agua Brava Lagoon in Mexico. In a series of studies, leaf area index (LAI) has been estimated using empirical relationships between ground-based measurements and VHR spectral vegetation indices or SAR back-scatter. Using IKONOS, Kovacs et al. (2004) found strong significant relationships between LAI of red and white mangroves and the Simple Ratio (SR) and the Normalized Difference Vegetation Index (NDVI). Both indices produced similar results; NDVI explained 71% of variance in LAI with a standard error of 0.63 while SR explained 73% of variance with a standard error of 0.65. In a follow-up study on black mangroves, Kovacs et al. (2005) found similar results – NDVI and SR explained 63% and 65% of LAI variance, respectively. The extent of saturation effects for the remote sensing of LAI in mangroves is unknown. While Green et al. (1997) reported LAI values from 0.8 to 7.0, other studies have not observed high LAI values associated with saturation effects (Heumann et al., unpublished data; Kovacs et al., 2004). While Kovacs et al. (2004) observed relatively high uncertainty for low LAI values, Kovacs et al. (2005) reported similar uncertainty for both healthy and degraded mangrove forests. Kovacs et al. (2009) used spectral vegetation indices from the Quickbird sensor and found very similar results to previous IKONOS studies. Kovacs et al., (2008) found a stronger relationship between cross-polarmetric C-Band SAR data and LAI ($r^2 = 0.82$) than previous VHR spectral relationships. Despite the strength of these findings, the study site of these studies is relatively species poor and much of the study area is degraded, according to the authors. These methods should therefore be replicated in other areas to test the consistency and variability of these empirical relationships across species and conditions.

VIII Height and biomass

Estimates of tree and forest biomass provide valuable insights into the carbon storage and cycling in forests (Litton et al., 2007). Canopy height and biomass have been shown in field studies to be strongly related for many mangrove species (Fromard et al., 1998; Smith and Whelan, 2006). Biomass can be estimated directly using PolSAR or indirectly using VHR image texture to dectect canopy structure or SAR Interferometry (InSAR), stereo imagery, or LiDAR to estimate canopy height.

Proisy et al. (2007) used Fourier-based textual ordination (i.e. principal components analysis of Fourier spectra) with IKONOS near-infrared and panchromatic imagery to estimate biomass based on detection of canopy structure. Results show a significant non-linear relationship between the tree stage (e.g. pioneer, mature, dead) and the principal components of the Fourier spectra. The best model used the panchromatic imagery with a 30 m window and explained over 90% of the total and trunk biomass with a relative error of 16.9%. The authors note that they did not find any 'saturation effect' at high biomass levels, often observed in spectral response of dense terrestrial vegetation (Huete et al., 1997).

Most studies that estimate height or biomass from satellite remote sensing use SAR. Several studies have used airborne SAR sensors, such as AIRSAR, to demonstrate the potential of SAR to estimate canopy characteristics (Lucas et al., 2007; Mougin et al., 1999; Proisy et al., 2000, 2002). PolSAR methods use the values and differences of horizontal, vertical, and cross polarizations as the SAR signal scatters and reflects with different forest components. For example, reflection off trunks and soil may produce a single or double bounce interactions while the signal may scatter within the canopy, which is dependent on the signal wavelength (Proisy et al., 2000). The P-band PolSAR best estimates tree height and above-ground biomass, although the HV polarization of L-band SAR also performs well, explaining 93%, 96%, and 94% of basal area, tree height, and above-ground biomass, respectively (Mougin et al., 1999). The relationships between PolSAR coefficients and biomass are, however, non-linear and change sign multiple times over the biomass range. In a follow-up study by Proisy et al. (2000), PolSAR signal modeling illustrated difficulties predicting the interaction of PolSAR with three-dimentional heterogeneous components, specifically interactions between soil surface, trunk, and canopy volume components. These findings were confirmed by Proisy et al. (2002). In pioneer and declining mangrove stands, a substantial fraction of scattering was due to the interaction of surface and canopy volume components. For example, between 30% and 90% of the scattering mechanism of L-band PolSAR was associated with the interactive component, depending upon the polarization and stand characteristics. Proisy et al. (2002) conclude based on model results that statistical relationships of PolSAR to biomass are limited to homogeneous closed canopies where interaction effects are less pronounced. In a separate study using AIRSAR to assess the potential of space-borne L-band PolSAR, Lucas et al. (2007) note that L-band HV data can delineate different mangrove zones based on species and biomass/stage, but that the separation of surface, volume, and interaction components from the PolSAR signal remains a significant challenge due to inconsistent empirical results. The implications of these results suggest that a given SAR signal results from different combinations of forest structure. Although Li et al. (2007) are able to separate surface and trunk components of Radarsat-1 imagery (C-Band, HH) using a genetic algorithm, the SAR data only explained about 45% of biomass variance, although these results were better than NDVI as a predictor of biomass.

A different SAR technique is InSAR. InSAR can produce millimeter accurate digital surface models of bare terrain by analyzing the signal phase between two offset SAR images (e.g. tandem sensors or repeat-track image acquisition). For additional information on InSAR, see Hanssen (2001) or Rott (2009). While InSAR is widely used in geology for high accuracy topographic mapping of volcanic and earthquake deformation, it can also be used to estimate canopy height. Under the assumption that the ground elevation is at mean sea level as all mangroves must grow in intertidal conditions, InSAR can be used to create a digital surface model of the canopy surface from which canopy height can be estimated (Fatoyinbo et al., 2008; Mitchell et al., 2007; Simard et al., 2006, 2008). InSAR processing for vegetation studies can be very complicated and difficult due to an often low coherence (i.e. agreement in signal phase) between images due to inconsistent scattering in the canopy volume. A globally available InSAR digital surface model, the Shuttle Topographic Radar Mission (SRTM) data set, has been demonstrated to provide reasonable estimates of mangrove canopy heights (Fatoyinbo et al., 2008; Simard et al., 2006, 2008). While the SRTM DSM can be calibrated using field measurements (Fatoyinbo et al., 2008; Simard et al., 2008), air borne LiDAR (Simard et al., 2006) or space-borne LiDAR from IceSAT/GLAS (Simard et al., 2008) can better characterize the vertical canopy structure.

The accuracy of this approach is best for tall mature mangroves where the relative error is less (Simard et al., 2006) as the reported root-mean square error ranges from 1.5 to 2.0 m, well within local topographic ranges within the intertidal zone. All three studies use a generalized allometric relationship to convert canopy height to standing biomass, because species information was unavailable. While the SRTM product has a spatial resolution of 30 m over the United States, global coverage is reduced to 90 m, limiting its applicability to very large homogenous mangroves.

IX Productivity

Mangroves can be as productive as terrestrial rainforests, yet productivity can vary greatly due to environmental conditions (Komiyama et al., 2008; Lovelock et al., 2004). While many field and greenhouse studies have investigated the rate and mechanisms of mangrove productivity, practically no research has been conducted to map mangrove productivity. In a field study using a hand-held spectroradiometer, Nichol et al. (2006) found a significant relationship between Photochemical Reflectance Index (PRI) and effective quantum yield, a metric of photosynthetic activity, thus demonstrating the potential for hyperspectral remote sensing of mangrove photosynthesis and productivity. In a similar study, Song et al. (forthcoming) found that there was a significant relationship between soil-water salinity and PRI, further suggesting the potential of remote sensing to detect productivity and stress in mangroves.

X Conclusions and future opportunities

Recent advances in the remote sensing of mangroves have demonstrated practical methods to improve classification accuracy, estimate leaf area, map individual species, and measure canopy height impossible with traditional remote sensing approaches. Newer types of imagery such as VHR and SAR provide new types of data which can be used separately or in conjunction with traditional remote sensing data. New techniques have been developed to exploit new types of data from VHR and SAR. Spatial patterns measured using image texture metrics or lacunarity can be related to canopy structure to detect individual species. InSAR has been used to directly measure canopy height and indirectly estimate standing biomass via allometric relationships. OBIA has been shown to outperform traditional pixel-based classifications in many cases and provides an environment in which other techniques such as data fusion and hierarchical rule-based classifications can be developed and applied. The science for remote sensing of mangroves has rapidly advanced in the last decade. Many of the challenges are not unique to mangroves and have been identified as challenges in other applications of terrestrial remote sensing (Wang et al., 2009). While recent advances have overcome many of the limitations of traditional remote sensing approaches, there remain many opportunities to further the science and application of mangrove remote sensing. The following is a list of suggested opportunities to improve and apply these advances.

1 Application of existing sensors

There are some existing sensors that have not been applied to mangrove remote sensing studies such as the Advanced Land Imager (ALI) and HYPERION on the EO-1 platform (see Table 3 for details). ALI is similar to the Landsat TM and ETM sensors with additional bands in the blue, NIR and SWIR. Although the spatial resolution of this sensor is relatively coarse, it can serve as a Landsat-compatible sensor for change-detection given the sensor malfunctions of Landsat ETM+ (e.g. scan line corrector) and ASTER (e.g. SWIR sensor). Of interest is the hyperspectral HYPERION sensor. HYPERION has 220 bands in the visible, NIR, and SWIR spectra. Given that HYPERION has been used to detect tree genera or species in tropical environments (e.g Christian and Krishnayya, 2009; Papes et al., 2010; Walsh et al., 2008) and laboratory studies have been able to distinguish between mangrove studies using hypserspectral imaging (Vaiphasa et al., 2005, 2007), there is great potential for mapping individual species using hyperspectral imagery. Furthermore, hyperspectral remote sensing could be used to estimate photosynthetic productivity and forest health (e.g. Nichol et al., 2006) as has been done for other tropical environments (e.g. Asner et al., 2006). Due to the relatively coarse spatial resolution of the HYPERION sensor (i.e. 30 m), spectral unmixing techniques will be required to reduce the effects of mixed pixel components

(Walsh et al., 2008) such as soil, water, shadow, and various mangrove species.

2 Use of existing methods from terrestrial forests

There are a number of remote sensing methods that have been developed for terrestrial forests that have not been adapted or tested for mangroves. For example, image texture has been used to estimate canopy structure and leaf area in temperate terrestrial forests (e.g. Colombo et al., 2003; Song and Dickinson, 2008; Wulder et al., 1998). While image texture has been used to map mangrove species, it has not been tested for other forest characteristics. Similarly, spectral unmixing techniques are often used in the remote sensing of terrestrial forests to separate the spectral end-members of mixed pixels. While studies have investigated the effect of background end-members (e.g. soil and water) on vegetation indices in mangrove forests (Diaz and Blackburn, 2003), to date there has not been a study that applies spectral unmixing to the remote sensing of mangrove forests. Finally, although considerable research has been conducted to develop process-based algorithms to model biophysical parameters such as LAI (Liang, 2007), these algorithms have not been applied to the remote sensing of mangroves.

3 Investigation of new sensors

The launch of several new sensors (e.g. ALOS PALSAR and PRISM, Radarsat-2, Worldview-2 and GeoEye-1) offer new opportunities (see Tables 3 and 4 for sensor details). ALOS PALSAR is an L-band PolSAR sensor with 10–30 m resolution, depending on polarization. L-band PolSAR has been demonstrated to be among the best SAR configurations to map mangrove structure. Furthermore, the ALOS PALSAR mission seeks repeat-track image acquisition, ideal for InSAR and relatively high resolution mapping of mangrove height compared to the 90 m global SRTM product. However, there remain challenges in obtaining high coherence between images within the canopy due to the relatively high transmittance of L-band SAR though the forest canopy (Rott, 2009).

Radarsat-2 is another new PolSAR sensor. Radarsat-2 is a C-band sensor with the option for very high spatial resolution imagery as fine as 1 m. Some of the previous challenges to SAR remote sensing are reduction in image ‘speckling’ from signal noise and mixed pixels. The very high resolution imagery from Radarsat-2 may reduce the effect of both of these effects. However, the potential for mangrove studies is limited as C-band PolSAR has been shown to be the least sensitive to mangrove canopy structure compared to other SAR wavelengths (e.g. Mougin et al., 1999), although the potential for high resolution InSAR applications exceed that of ALOS PALSAR in term of spatial resolution.

Another potential sensor for mapping mangrove canopy height is ALOS PRISM. PRISM is a very high resolution panchromatic sensor (e.g. 2.5 m) that acquires triplet sets of images (e.g. front, nadir, backward) for stereo DEM extraction. While this method has a lower vertical accuracy than InSAR, stereo methods of DEM extraction are relatively simple and are available with many commercial remote sensing software packages.

A new generation of VHR sensors has recently been launched as a continuation of the legacy of IKONOS and Quickbird. The successor of IKONOS, GeoEye-1, has four multispectral bands with a multispectral spatial resolution of 1.65 m and a panchromatic resolution of 0.41 m. The improved spatial resolution (i.e. less than half the pixel size of IKONOS), provides new opportunities of further investigation of spatial information in mangrove remote sensing using image texture, lacunarity, and image segmentation in OBIA. The successor to Quickbird, Worldview-2, has similar spatial resolutions to GeoEye-1 (less than 2 m in the multispectral and less than 0.5 m in the panchromatic bands, but finer resolutions are restricted by the US government), but has eight multispectral channels including bands in the yellow and red edge spectral ranges designed for vegetation studies. However, since both new VHR sensors have only recently been launched, the amount of archive imagery is relatively small and the cost of tasking image acquisition is very high compared to other remote sensing imagery.

4 Data fusion and integration

Data fusion is a promising methodology that aims to reduce data limitations by integrating multiple types of data. While data fusion has been used for mangrove studies to improve classification accuracy (Wang and Sousa-Filho, 2009), data fusion has yet to be incorporated into other areas of mangrove remote sensing such as mapping canopy height or stand biomass. The current dominant technique for mapping canopy height is SRTM elevation data. This product can have a high vertical accuracy in flat terrain (Gorokhovich and Voustianiouk, 2006) but has a coarse resolution (e.g. 90 m) outside the United States where the vast majority of mangrove occurs. A less common approach outlined in the previous section uses stereo optical imagery to extract a DEM. While this approach is generally less accurate than InSAR techniques, the spatial resolution is potentially much higher, especially when VHR imagery is used. Furthermore, a global 30 m DEM product using the ASTER sensor was recently released by NASA. Fusion of DEM data from optical stereo imagery such as ASTER or ALOS PRISM with coarse resolution SRTM data could integrate the strengths of both data sets. High resolution canopy height maps can also help improve classification accuracy using a data fusion approach in OBIA (e.g. Ke et al., 2010) to distinguish between mangrove stages and species. Another opportunity is the fusion of species and canopy structure data. Mangrove trees have strong allometric relationships (e.g. canopy height versus biomass or leaf area), but these relationships vary by species (e.g. Smith and Whelan, 2006). Previous studies have relied on generalized allometric relationships. For example, Simard et al. (2006) estimate aboveground biomass based on canopy height. The fusion of species maps and canopy height could improve this technique through the use of species-specific allometric relationships.

5 Monitoring: Local to global

Perhaps the greatest challenge, and yet the greatest opportunity, is global monitoring of mangroves. To date, most studies have focused on local monitoring, although a few studies have provided regional assessments of South Asia. These local and regional monitoring projects are very important to their locals, but their scope is limited. Recently, Giri et al. (2010) mapped mangroves globally for the first time exclusively using satellite remote sensing data. This work demonstrates substantial advancement toward global monitoring efforts. Global monitoring will not only provide a comprehensive overview of the state and change of mangroves, but will also provide consistent data between regions to help track not only mangrove extent, but structure, function, and maybe even ecosystem services as well. In order to achieve global monitoring, the following steps are needed:

(1) *Transition from experimentation to application.* Traditional remote sensing data and techniques are now regularly applied through the world for mangrove studies. However, traditional remote sensing has many serious limitations. Recent advances also need to be incorporated into applied studies to provide improved monitoring.
(2) *Collaboration among scientists.* Collaboration is needed between remote sensing specialist for fusion and integration of different types of remote sensing such as PolSAR, InSAR and VHR spatial

imagery into accessible and available products. Furthermore, to advance the links between remote sensing and ecology, increased collaboration is needed between field and remote sensing scientists (Newton et al., 2009) as field inventory is a critical component for the calibration, validation, and interpretation of remote sensing products.

(3) *Wide-scale data acquisition.* Although global coverage is not necessary for moni toring purposes as a targeted sampling scheme could produce good assessment, data acquisition must be pan-tropical to cover different types of mangroves. Furthermore, repeated image acquisition is required to produce time series of imagery to understand the dynamics of change, rather than just snapshots of change (Gillanders et al., 2008).

(4) *The digital divide.* The vast majority of the world's mangroves exist in developing nations. While some developing nations like India and Brazil have produced their own satellite remote sensing programs, most nations rely on the developed nations for access to remote sensing technology, not to mention barriers due to the costs of infrastructure and training. While Dahdouh-Guebas et al. (2006) show that aerial photography can provide inexpensive high quality data, satellite based remote sensing has greater potential for coverage, repeatability, and consistency. While free access to imagery for scientific has improved in recent years (e.g. the Landsat archive, or to certain developing nations the China-Brazil Earth Resources Satellite), more effort is needed to improve training in remote sensing techniques and provide accessibility to remote sensing imagery, products, and requisite technology such as software and computers to scientists in the developing world.

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References

Al Habshi A, Youssef T, Aizpuru M, and Blasco F (2007) New mangrove ecosystem data along the UAE coast using remote sensing. *Aquatic Ecosystem Health and Management* 10: 309–319.

Alongi DM (2002) Present state and future of the world's mangrove forests. *Environmental Conservation* 29: 331–349.

Asner GP, Martin RE, Carlson KM, Rascher U, and Vitousek PM (2006) Vegetation-climate interactions among native and invasive species in Hawaiian rainforest. *Ecosystems* 9: 1106–1117.

Barber DG and Ledrew EF (1991) SAR sea ice discrimination using texture statistics – a multivariate approach. *Photogrammetric Engineering and Remote Sensing* 57(4): 385–395.

Beland M, Goita K, Bonn F, and Pham TTH (2006) Assessment of land-cover changes related to shrimp aquaculture using remote sensing data: A case study in the Giao Thuy District, Vietnam. *International Journal of Remote Sensing* 27: 1491–1510.

Benfield SL, Guzman HM, and Mair JM (2005) Temporal mangrove dynamics in relation to coastal development in Pacific Panama. *Journal of Environmental Management* 76: 263–276.

Bhatt S, Shah DG, and Desai N (2009) The mangrove diversity of Purna Estuary, South Gujarat, India. *Tropical Ecology* 50: 287–293.

Chauvaud S, Bouchon C, and Maniere R (1998) Remote sensing techniques adapted to high resolution mapping of tropical coastal marine ecosystems (coral reefs, seagrass beds and mangrove). *International Journal of Remote Sensing* 19: 3625–3639.

Chauvaud S, Bouchon C, and Maniere R (2001) Thematic mapping of tropical marine communities (coral reefs, seagrass beds and mangroves) using SPOT data in Guadeloupe Island. *Oceanologica Acta* 24: S3–S16.

Christian B and Krishnayya NSR (2009) Classification of tropical trees growing in a sanctuary using Hyperion

(EO-1) and SAM algorithm. *Current Science* 96: 1601–1607.

Colombo R, Bellingeri D, Fasolini D, and Marino CM (2003) Retrieval of leaf area index in different vegetation types using high resolution satellite data. *Remote Sensing of Environment* 86: 120–131.

Conchedda G, Durieux L, and Mayaux P (2008) An object-based method for mapping and change analysis in mangrove ecosystems. *ISPRS Journal of Photogrammetry and Remote Sensing* 63: 578–589.

Cornejo RH, Koedam N, Luna AR, Troell M, and Dahdouh-Guebas F (2005) Remote sensing and ethnobotanical assessment of the mangrove forest changes in the Navachiste-San Ignacio-Macapule lagoon complex, Sinaloa, Mexico. *Ecology and Society* 10: 16.

Costanza R, dArge R, deGroot R, Farber S, Grasso M, Hannon B, et al. (1997) The value of the world's ecosystem services and natural capital. *Nature* 387: 253–260.

Crist EP and Cicone RC (1984) Application of the Tasseled Cap Concept to simulated thematic mapper data. *Photogrammetric Engineering and Remote Sensing* 50: 343–352.

Dahdouh-Guebas F, Verheyden A, Kairo JG, Jayatissa LP, and Koedam N (2006) Capacity building in tropical coastal resource monitoring in developing countries: A re-appreciation of the oldest remote sensing method. *International Journal of Sustainable Development and World Ecology* 13: 62–76.

Diaz BM and Blackburn GA (2003) Remote sensing of mangrove biophysical properties: Evidence from a laboratory simulation of the possible effects of background variation on spectral vegetation indices. *International Journal of Remote Sensing* 24: 53–73.

D'Iorio M, Jupiter SD, Cochran SA, and Potts DC (2007) Optimizing remote sensing and GIS tools for mapping and managing the distribution of an invasive mangrove (*Rhizophora mangle*) on South Molokai, Hawaii. *Marine Geodesy,* 30: 125–144.

Doyle TW, Krauss KW, and Wells CJ (2009) Landscape analysis and pattern of hurricane impact and circulation mangrove forests of the Everglades. *Wetlands* 29: 44–53.

Duarte CM and Cebrian J (1996) The fate of marine autotrophic production. *Limnology and Oceanography* 41: 1758–1766.

Duke NC, Ball MC, and Ellison JC (1998) Factors influencing biodiversity and distributional gradients in mangroves. *Global Ecology and Biogeography Letters* 7: 27–47.

Dvorak M, Vargas H, Fessl B, and Tebbich S (2004) On the verge of extinction: A survey of the mangrove finch *Cactospiza heliobates* and its habitat on the Galapagos Islands. *Oryx* 38: 171–179.

Ellison AM (2002) Macroecology of mangroves: Large-scale patterns and processes in tropical coastal forests. *Trees – Structure and Function* 16: 181–194.

Erftemeijer PLA (2002) A new technique for rapid assessment of mangrove degradation: A case study of shrimp farm encroachment in Thailand. *Trees – Structure and Function* 16: 204–208.

Eslami-Andargoli L, Dale P, Sipe N, and Chaseling J (2009) Mangrove expansion and rainfall patterns in Moreton Bay, Southeast Queensland, Australia. *Estuarine Coastal and Shelf Science* 85: 292–298.

Everitt JH, Yang C, Summy KR, Judd FW, and Davis MR (2007) Evaluation of color-infrared photography and digital imagery to map black mangrove on the Texas gulf coast. *Journal of Coastal Research* 23: 230–235.

Ewel KC, Zheng SF, Pinzon ZS, and Bourgeois JA (1998) Environmental effects of canopy gap formation in high-rainfall mangrove forests. *Biotropica* 30: 510–518.

Farnsworth EJ (1998) Issues of spatial, taxonomic and temporal scale in delineating links between mangrove diversity and ecosystem function. *Global Ecology and Biogeography Letters* 7: 15–25.

Fatoyinbo TE, Simard M, Washington-Allen RA, and Shugart HH (2008) Landscape-scale extent, height, biomass, and carbon estimation of Mozambique's mangrove forests with Landsat ETM+ and Shuttle Radar Topography Mission elevation data. *Journal of Geophysical Research – Biogeosciences* 113: G02S06.

Fromard F, Puig H, Mougin E, Marty G, Betoulle JL, and Cadamuro L (1998) Structure, above-ground biomass and dynamics of mangrove ecosystems: New data from French Guiana. *Oecologia* 115: 39–53.

Fromard F, Vega C, and Proisy C (2004) Half a century of dynamic coastal change affecting mangrove shorelines of French Guiana: A case study based on remote sensing data analyses and field surveys. *Marine Geology* 208: 265–280.

Gao J (1998) A hybrid method toward accurate mapping of mangroves in a marginal habitat from SPOT multispectral data. *International Journal of Remote Sensing* 19: 1887–1899.

Gao J (1999) A comparative study on spatial and spectral resolutions of satellite data in mapping mangrove forests. *International Journal of Remote Sensing* 20: 2823–2833.

Gao J, Chen HF, Zhang Y, and Zha Y (2004) Knowledge-based approaches to accurate mapping of mangroves from satellite data. *Photogrammetric Engineering and Remote Sensing* 70: 1241–1248.

Gillanders SN, Coops NC, Wulder MA, Gergel SE, and Nelson T (2008) Multitemporal remote sensing of landscape dynamics and pattern change: Describing natural and anthropogenic trends. *Progress in Physical Geography* 32: 503–528.

Gillespie TW, Foody GM, Rocchini D, Giorgi AP, and Saatchi S (2008) Measuring and modelling biodiversity from space. *Progress in Physical Geography* 32: 203–221.

Giri C, Ochieng E, Tieszen LL, Zhu Z, Singh A, Loveland T, et al. (2010) Status and distribution of mangrove forests of the world using earth observation satellite data. *Global Ecology and Biography.* doi: 10.1111/j.1466-8238.2010.00584.x.

Giri C, Pengra B, Zhu ZL, Singh A, and Tieszen LL (2007) Monitoring mangrove forest dynamics of the Sundarbans in Bangladesh and India using multi-temporal satellite data from 1973 to 2000. *Estuarine Coastal and Shelf Science* 73: 91–100.

Giri C, Zhu Z, Tieszen LL, Singh A, Gillette S, and Kelmelis JA (2008) Mangrove forest distributions and dynamics (1975–2005) of the tsunami-affected region of Asia. *Journal of Biogeography* 35: 519–528.

Gopal B and Chauhan M (2006) Biodiversity and its conservation in the Sundarban Mangrove Ecosystem. *Aquatic Sciences* 68: 338–354.

Gorokhovich Y and Voustianiouk A (2006) Accuracy assessment of the processed SRTM-based elevation data by CGIAR using field data from USA and Thailand and its relation to the terrain characteristics. *Remote Sensing of Environment* 104(4): 409–415.

Green EP, Clark CD, Mumby PJ, Edwards AJ, and Ellis AC (1998) Remote sensing techniques for mangrove mapping. *International Journal of Remote Sensing* 19: 935–956.

Green EP, Mumby PJ, Edwards AJ, Clark CD, and Ellis AC (1997) Estimating leaf area index of mangroves from satellite data. *Aquatic Botany* 58: 11–19.

Hanssen RF (2001) *Data Interpretation and Error Analysis*. Dordrecht: Kluwer Academic.

Haralick RM, Shanmuga K, and Dinstein I (1973) Textural features for image classification. *IEEE Transactions on Systems Man and Cybernetics* SMC3: 610–621.

Henderson FM and Lewis AJ (eds) (1998) *Principles and Applications of Imaging Radar*. New York: Wiley.

Hogarth P (2007) *The Biology of Mangroves and Seagrasses*. Oxford: Oxford University Press.

Hossain MZ, Tripathi NV, and Gallardo WG (2009) Land use dynamics in a marine protected area system in lower andaman coast of Thailand, 1990–2005. *Journal of Coastal Research* 25: 1082–1095.

Howari FM, Jordan BR, Bouhouche N, and Wyllie-Echeverria S (2009) Field and remote-sensing assessment of mangrove forests and seagrass beds in the northwestern part of the United Arab Emirates. *Journal of Coastal Research* 25: 48–56.

Huang X, Zhang LP, and Wang L (2009) Evaluation of morphological texture features for mangrove forest mapping and species discrimination using multispectral IKONOS imagery. *IEEE Geoscience and Remote Sensing Letters* 6: 393–397.

Huete AR, Liu HQ, Batchily K, and van Leeuwen W (1997) A comparison of vegetation indices over a global set of TM images for EOS-MODIS. *Remote Sensing of Environment* 59: 440–451.

Islam MA, Thenkabail PS, Kulawardhana RW, Alankara R, Gunasinghe S, Edussriya C, et al. (2008) Semi-automated methods for mapping wetlands using Landsat ETM plus and SRTM data. *International Journal of Remote Sensing* 29: 7077–7106.

James GK, Adegoke JO, Saba E, Nwilo P, and Akinyede J (2007) Satellite-based assessment of the extent and changes in the mangrove ecosystem of the Niger Delta. *Marine Geodesy* 30: 249–267.

Jones J, Dale PER, Chandica AL, and Breitfuss MJ (2004) Changes in the distribution of the grey mangrove *Avicennia marina* (Forsk.) using large scale aerial color infrared photographs: Are the changes related to habitat modification for mosquito control? *Estuarine Coastal and Shelf Science* 61: 45–54.

Kayitakire F, Hamel C, and Defourny P (2006) Retrieving forest structure variables based on image texture analysis and IKONOS-2 imagery. *Remote Sensing of Environment* 102 (3–4): 390–401.

Ke YH, Quackenbush LJ, and Im J (2010) Synergistic use of QuickBird multispectral imagery and LIDAR data for object-based forest species classification. *Remote Sensing of Environment* 114: 1141–1154.

Kercher JR and Chambers JQ (2001) Parameter estimation for a global model of terrestrial biogeochemical cycling by an iterative method. *Ecological Modelling* 139: 137–175.

Komiyama A, Ong JE, and Poungparn S (2008) Allometry, biomass, and productivity of mangrove forests: A review. *Aquatic Botany* 89: 128–137.

Kovacs JM, Flores-Verdugo F, Wang JF, and Aspden LP (2004) Estimating leaf area index of a degraded mangrove forest using high spatial resolution satellite data. *Aquatic Botany* 80: 13–22.

Kovacs JM, King JML, de Santiago FF, and Flores-Verdugo F (2009) Evaluating the condition of a mangrove forest of the Mexican Pacific based on an estimated leaf area index mapping approach. *Environmental Monitoring and Assessment* 157: 137–149.

Kovacs JM, Vandenberg CV, Wang J, and Flores-Verdugo F (2008) The use of multipolarised spaceborne SAR backscatter for monitoring the health of a degraded mangrove forest. *Journal of Coastal Research* 24: 248–254.

Kovacs JM, Wang JF, and Flores-Verdugo F (2005) Mapping mangrove leaf area index at the species level using IKONOS and LAI-2000 sensors for the Agua Brava Lagoon, Mexican Pacific. *Estuarine Coastal and Shelf Science* 62: 377–384.

Krause G, Bock M, Weiers S, and Braun G (2004) Mapping land-cover and mangrove structures with remote sensing techniques: A contribution to a synoptic GIS in support of coastal management in North Brazil. *Environmental Management* 34: 429–440.

Laegdsgaard P and Johnson C (2001) Why do juvenile fish utilise mangrove habitats? *Journal of Experimental Marine Biology and Ecology* 257: 229–253.

Lee SY (1999) Tropical mangrove ecology: Physical and biotic factors influencing ecosystem structure and function. *Australian Journal of Ecology* 24: 355–366.

Lee TM and Yeh HC (2009) Applying remote sensing techniques to monitor shifting wetland vegetation: A case study of Danshui River estuary mangrove communities, Taiwan. *Ecological Engineering* 35: 487–496.

Li X, Yeh AGO, Wang S, Liu K, Liu X, Qian J, et al. (2007) Regression and analytical models for estimating mangrove wetland biomass in South China using Radarsat images. *International Journal of Remote Sensing* 28: 5567–5582.

Liang SL (2007) Recent developments in estimating land surface biogeophysical variables from optical remote sensing. *Progress in Physical Geography* 31: 501–516.

Litton CM, Raich JW, and Ryan MG (2007) Carbon allocation in forest ecosystems. *Global Change Biology* 13: 2089–2109.

Liu K, Li X, Shi X, and Wang SG (2008) Monitoring mangrove forest changes using remote sensing and GIS data with decision-tree learning. *Wetlands* 28: 336–346.

Long BG and Skewes TD (1996) A technique for mapping mangroves with Landsat TM satellite data and Geographic Information System. *Estuarine Coastal and Shelf Science* 43: 373–381.

Lovelock CE, Feller IC, McKee KL, Engelbrecht BMJ, and Ball MC (2004) The effect of nutrient enrichment on growth, photosynthesis and hydraulic conductance of dwarf mangroves in Panama. *Functional Ecology* 18: 25–33.

Lucas RM, Mitchell AL, Rosenqvist A, Proisy C, Melius A, and Ticehurst C (2007) The potential of L-band SAR for quantifying mangrove characteristics and change: Case studies from the tropics. *Aquatic Conservation – Marine and Freshwater Ecosystems* 17: 245–264.

Manson FJ, Loneragan NR, McLeod IM, and Kenyon RA (2001) Assessing techniques for estimating the extent of mangroves: Topographic maps, aerial photographs and Landsat TM images. *Marine and Freshwater Research* 52: 787–792.

Mantri VA and Mishra AK (2006) On monitoring mangrove vegetation of Sagar Island by remote sensing. *National Academy Science Letters – India* 29: 45–48.

Mitchell AL, Lucas RM, Donnelly BE, Pfitzner K, Milne AK, and Finlayson M (2007) A new map of mangroves for Kakadu National Park, Northern Australia, based on stereo aerial photography. *Aquatic Conservation – Marine and Freshwater Ecosystems* 17: 446–467.

Mougin E, Proisy C, Marty G, Fromard F, Puig H, Betoulle JL, et al. (1999) Multifrequency and multipolarization radar backscattering from mangrove forests. *IEEE Transactions on Geoscience and Remote Sensing* 37: 94–102.

Mumby PJ, Edwards AJ, Arias-Gonzalez JE, Lindeman KC, Blackwell PG, Gall A, et al. (2004) Mangroves enhance the biomass of coral reef fish communities in the Caribbean. *Nature* 427: 533–536.

Mumby PJ, Green EP, Edwards AJ, and Clark CD (1999) The cost-effectiveness of remote sensing for tropical coastal resources assessment and management. *Journal of Environmental Management* 55: 157–166.

Murray MR, Zisman SA, Furley PA, Munro DM, Gibson J, Ratter J, et al. (2003) The mangroves of Belize. Part 1. Distribution, composition and classification. *Forest Ecology and Management* 174: 265–279.

Myint SW, Giri CP, Le W, Zhu ZL, and Gillette SC (2008) Identifying mangrove species and their surrounding land use and land cover classes using an object-oriented approach with a lacunarity spatial measure. *GIScience and Remote Sensing* 45: 188–208.

Nagelkerken I, Blaber SJM, Bouillon S, Green P, Haywood M, Kirton LG, et al. (2008) The habitat function of mangroves for terrestrial and marine fauna: A review. *Aquatic Botany* 89: 155–185.

Neukermans G, Dahdouh-Guebas F, Kairo JG, and Koedam N (2008) Mangrove species and stand mapping in GAzi bay (Kenya) using Quickbird satellite imagery. *Journal of Spatial Science* 53: 75–86.

Newton AC, Hill RA, Echeverria C, Golicher D, Benayas JMR, Cayuela L, and Hinsley SA (2009) Remote sensing and the future of landscape ecology. *Progress in Physical Geography* 33: 528–546.

Nichol CJ, Rascher U, Matsubara S, and Osmond B (2006) Assessing photosynthetic efficiency in an experimental mangrove canopy using remote sensing and chlorophyll fluorescence. *Trees-Structure and Function* 20: 9–15.

Olwig MF, Sorensen MK, Rasmussen MS, Danielsen F, Selvam V, Hansen LB, et al. (2007) Using remote sensing to assess the protective role of coastal woody vegetation against tsunami waves. *International Journal of Remote Sensing* 28: 3153–3169.

Onuf CP, Teal JM, and Valiela I (1977) Interactions of nutrients, plant-growth and herbivory in a mangrove ecosystem. *Ecology* 58: 514–526.

Paling EI, Kobryn HT, and Humphreys G (2008) Assessing the extent of mangrove change caused by Cyclone Vance in the eastern Exmouth Gulf, northwestern Australia. *Estuarine Coastal and Shelf Science* 77: 603–613.

Papes M, Tupayachi R, Martinez P, Peterson AT, and Powell GVN (2010) Using hyperspectral satellite imagery for regional inventories: A test with tropical emergent trees in the Amazon Basin. *Journal of Vegetation Science* 21: 342–354.

Pasher J, King D, and Lindsay K (2007) Modelling and mapping potential hooded warbler (*Wilsonia citrina*) habitat using remotely sensed imagery. *Remote Sensing of Environment* 107: 471–483.

Pasqualini V, Iltis J, Dessay N, Lointier M, Guelorget O, and Polidori L (1999) Mangrove mapping in north-western Madagascar using SPOT-XS and SIR-C radar data. *Hydrobiologia* 413: 127–133.

Pattanaik C, Reddy CS, and Prasad SN (2008) Mapping, monitoring and conservation of Mahanandi wetland ecosystem, Orissa, India using remote sensing and GIS. *Proceedings of the National Academy of Sciences India Section B – Biological Sciences* 78: 81–89.

Proisy C, Couteron P, and Fromard F (2007) Predicting and mapping mangrove biomass from canopy grain analysis using Fourier-based textural ordination of IKONOS images. *Remote Sensing of Environment* 109: 379–392.

Proisy C, Mougin E, Fromard F, and Karam MA (2000) Interpretation of polarimetric radar signatures of mangrove forests. *Remote Sensing of Environment* 71: 56–66.

Proisy C, Mougin E, Fromard F, Trichon V, and Karam MA (2002) On the influence of canopy structure on the radar backscattering of mangrove forests. *International Journal of Remote Sensing* 23: 4197–4210.

Ramachandran S, Sundaramoorthy S, Krishnamoorthy R, Devasenapathy J, and Thanikachalam N (1998) Application of remote sensing and GIS to coastal wetland ecology of Tamil Nadu and Andaman and Nicobar group of islands with special reference to mangroves. *Current Science* 75: 236–244.

Ramsey EW and Jensen JR (1996) Remote sensing of mangrove wetlands: Relating canopy spectra to site-specific data. *Photogrammetric Engineering and Remote Sensing* 62: 939–948.

Rasolofoharinoro M, Blasco F, Bellan MF, Aizpuru M, Gauquelin T, and Denis J (1998) A remote sensing based methodology for mangrove studies in Madagascar. *International Journal of Remote Sensing* 19: 1873–1886.

Reddy CS and Pattanaik C (2007) Mangrove vegetation assessment and monitoring in Balasore district, Orissa using remote sensing and GIS. *National Academy Science Letters – India* 30: 377–381.

Rott H (2009) Advances in interferometric synthetic aperture radar (InSAR) in earth system science. *Progress in Physical Geography* 33: 769–791.

Ruiz-Luna A and Berlanga-Robles CA (2003) Land use, land cover changes and coastal lagoon surface reduction associated with urban growth in northwest Mexico. *Landscape Ecology* 18: 159–171.

Saito H, Bellan MF, Al-Habshi A, Aizpuru M, and Blasco F (2003) Mangrove research and coastal ecosystem studies with SPOT-4 HRVIR and TERRA ASTER in the Arabian Gulf. *International Journal of Remote Sensing* 24: 4073–4092.

Simard M, De Grandi G, Saatchi S, and Mayaux P (2002) Mapping tropical coastal vegetation using JERS-1 and ERS-1 radar data with a decision tree classifier. *International Journal of Remote Sensing* 23: 1461–1474.

Simard M, Rivera-Monroy VH, Mancera-Pineda JE, Castaneda-Moya E, and Twilley RR (2008) A systematic method for 3D mapping of mangrove forests based on Shuttle Radar Topography Mission elevation data, ICEsat/GLAS waveforms and field data: Application to Cienaga Grande de Santa Marta, Colombia. *Remote Sensing of Environment* 112: 2131–2144.

Simard M, Zhang KQ, Rivera-Monroy VH, Ross MS, Ruiz PL, Castaneda-Moya E, et al. (2006) Mapping height and biomass of mangrove forests in Everglades National Park with SRTM elevation data. *Photogrammetric Engineering and Remote Sensing* 72: 299–311.

Sirikulchayanon P, Sun WX, and Oyana TJ (2008) Assessing the impact of the 2004 tsunami on mangroves using remote sensing and GIS techniques. *International Journal of Remote Sensing* 29: 3553–3576.

Smith TJ III (1992) Forest structure. In Robertson AI and Alongi DM (eds) *Tropical Mangrove Ecosystems*. Washington, DC: American Geophysical Union, 101–136.

Smith TJ III and Whelan KRT (2006) Development of allometric relations for three mangrove species in South Florida for use in the Greater Everglades Ecosystem restoration. *Wetlands Ecology and Management* 14: 409–419.

Song C and Dickinson MB (2008) Extracting forest canopy structure from spatial information of high resolution optical imagery: Tree crown size versus leaf area index. *International Journal of Remote Sensing* 29: 5605–5622.

Song C, White B, and Heumann BW (forthcoming) Hyperspectral remote sensing of salinity stress on red (*Rhizophora mangle*) and white (*Laguncularia racemosa*) mangroves on Galapagos Islands. *Remote Sensing Letters*.

Souza-Filho PWM and Paradella WR (2003) Use of synthetic aperture radar for recognition of Coastal Geomorphological Features, land-use assessment and shoreline changes in Braganca coast, Para, Northern Brazil. *Anais da Academia Brasileira de Ciencias* 75: 341–356.

Souza-Filho PWM and Paradella WR (2005) Use of RADARSAT-1 fine mode and Landsat-5 TM selective principal component analysis for geomorphological mapping in a macrotidal mangrove coast in the Amazon region. *Canadian Journal of Remote Sensing* 31: 214–224.

Thu PM and Populus J (2007) Status and changes of mangrove forest in Mekong Delta: Case study in Tra Vinh, Vietnam. *Estuarine Coastal and Shelf Science* 71: 98–109.

Tomlinson PB (1986) *The Botany of Mangroves*. Cambridge: Cambridge University Press.

Vaiphasa C, Ongsomwang S, Vaiphasa T, and Skidmore AK (2005) Tropical mangrove species discrimination using hyperspectral data: A laboratory study. *Estuarine Coastal and Shelf Science* 65(1–2): 371–379.

Vaiphasa C, Skidmore AK, and de Boer WF (2006) A post-classifier for mangrove mapping using ecological data. *ISPRS Journal of Photogrammetry and Remote Sensing* 61: 1.

Vaiphasa C, Skidmore AK, de Boer WF, and Vaiphasa T (2007) A hyperspectral band selector for plant species discrimination. *ISPRS Journal of Photogrammetry and Remote Sensing* 62(3): 225–23.

Vasconcelos MJP, Biai JCM, Araujo A, and Diniz MA (2002) Land cover change in two protected areas of Guinea-Bissau (1956–1998). *Applied Geography* 22: 139–156.

Walsh SJ, McCleary AL, Mena CF, Shao Y, Tuttle JP, Gonzalez A, et al. (2008) QuickBird and Hyperion data analysis of an invasive plant species in the Galapagos Islands of Ecuador: Implications for control and land use management. *Remote Sensing of Environment* 112: 1927–1941.

Wang K, Franklin SE, Guo XL, He YH, and McDermid GJ (2009) Problems in remote sensing of landscapes and habitats. *Progress in Physical Geography* 33: 747–768.

Wang L and Sousa-Filho WP (2009) Distinguishing mangrove species with laboratory measurements of hyperspectral leaf reflectance. *International Journal of Remote Sensing* 30: 1267–1281.

Wang L, Silvan-Cardenas JL, and Sousa WP (2008) Neural network classification of mangrove species from multi-seasonal IKONOS imagery. *Photogrammetric Engineering and Remote Sensing* 74: 921–927.

Wang L, Sousa-Filho WP, and Gong P (2004a) Integration of object-based and pixel-based classification for mapping mangroves with IKONOS imagery. *International Journal of Remote Sensing* 25: 5655–5668.

Wang L, Sousa-Filho WP, Gong P, and Biging GS (2004b) Comparison of IKONOS and QuickBird images for mapping mangrove species on the Caribbean coast of Panama. *Remote Sensing of Environment* 91: 432–440.

Ward GA, Smith TJ, Whelan KRT, and Doyle TW (2006) Regional processes in mangrove ecosystems: Spatial scaling relationships, biomass, and turnover rates following catastrophic disturbance. *Hydrobiologia* 569: 517–527.

Wilkie ML and Fortuna S (2003) Status and trends in mangrove area extent worldwide. Forest Resources Assessment Working Paper 63. Rome: Forest Resources Division, Food and Agriculture Organization of the United Nations (FAO).

Wooster M (2007) Remote sensing: sensors and systems. *Progress in Physical Geography* 31: 95–100.

Wulder MA, LeDrew EF, Franklin SE, and Lavigne MB (1998) Aerial image texture information in the estimation of northern deciduous and mixed wood forest leaf area index (LAI). *Remote Sensing of Environment* 64: 64–76.

Yang CH, Everitt JH, Fletcher RS, Jensen RR, and Mausel PW (2009) Evaluating AISA plus hyperspectral imagery for mapping black mangrove along the South Texas Gulf Coast. *Photogrammetric Engineering and Remote Sensing* 75: 425–435.