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High resolution satellite imagery for tropical biodiversity studies: the devil is in the detail

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Abstract While high resolution satellite remote sensing has been hailed as a very useful source of data for biodiversity assessment and monitoring, applications have been more developed in temperate areas. The biodiverse tropics offer a challenge of an altogether different magnitude for hyperspatial and hyperspectral remote sensing. This paper examines issues related to hyperspatial and hyperspectral remotely sensed imagery, which constitutes one of the most potentially powerful yet underutilized sources of for tropical research on biodiversity. Hyperspatial data with their increased pixel resolution are possibly best suited at facilitating the accurate location of features such as tree canopies, but less suited to the identification of aspects such as species identity, particularly when spatial resolution becomes too fine and pixels are smaller than the size of the object (e.g., tree canopy) being identified. Hyperspectral data on the other hand, with their high spectral resolution, can be used to record information pertaining to a range of critical plant properties related to species identity, and can be very effective used for discriminating tree species in tropical forests, despite the greater complexity of such environments. There remains a glaring gap in the easy availability of hyperspectral and hyperspatial satellite data in the tropics due to reasons of cost, data coverage, and security restrictions. Stimulating discussion on the applications of this powerful, but underutilized tool by ecologists, is the first step in

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promoting a more extensive use of such data for ecological studies in tropical biodiversity rich areas.

Keywords Biodiversity · Hyperspatial data · Hyperspectral data · Monitoring · Remote sensing · Satellite imagery · Tropics

Rapid developments in satellite remote sensing have generated much enthusiasm about its potential as a powerful tool for ecological research. Yet, the results achieved have largely belied expectations (Innes and Koch 1998). While efforts have been made to utilize moderate spatial resolution satellites such as Landsat ETM+ and SPOT for ecological studies such as biodiversity estimation, these have achieved only moderate success, and provided conflicting outcomes (e.g., Jakubauskas and Price 1997; Verlinden and Masogo 1997; as also reviewed in Nagendra 2001). While such data are very valuable for the studies of human drivers of land cover change, being at an appropriate scale for such uses (Ostrom and Nagendra 2006), they are less useful for studies of biodiversity distribution. Increasingly, thus, the use of remote sensing became limited to purposes of habitat mapping and analyses of land cover change.

One of the major perceived limitations of satellite remote sensing platforms such as Landsat has been that of insufficient spatial and spectral resolution. However, as stated by Kerr and Ostrovsky (2003): '[the] perceived 'scale gap' is narrowing […] with the increasing availability of very high-resolution data that can be linked directly to traditional field ecological measurements'. Thus, in recent years, a rapid improvement in spectral and spatial resolution has ostensibly provided researchers with better means to link data from the sky with data from the field (Kerr and Ostrovsky 2003). The launch of very high spatial resolution satellite sensors like IKONOS (spatial resolution in the MS: 4 m), Quickbird (spatial resolution in the MS: 2.88 m), and OrbView-3 (spatial resolution in the MS: 4 m) as well as very high spectral resolution sensors such as Hyperion (196 bands) have therefore provided researchers with the opportunity to study ecological systems at far greater detail than previously possible (e.g., Levin et al. 2007; Rocchini 2007). These data have been used for a range of ecological applications including studies of logging impact assessment (Read et al. 2003), upland vegetation monitoring (Mehner et al. 2004), biomass modeling (Thenkabail et al. 2004), species richness estimations (Levin et al. 2007; Rocchini 2007), landscape multi-temporal analysis (Im et al. 2007), forest and wetland classification (Kayitakire et al. 2006; Johansen et al. 2007; Laba et al. 2008), urban vegetation life form estimation (Nichol and Wong 2007), and land cover fractional mapping (Olthof and Fraser 2007).

Yet, despite the rapid improvements in remote sensing technologies, an old problem continues to persist. Temperate areas have seen much greater development and application of these new technologies for ecological research, while applications in the tropics continue to lag behind (Nagendra 2001; Sanchez-Azofeifa et al. 2003; Townsend et al. 2008). Temperate landscapes offer a more manageable location for such studies, with a relatively small number of habitat types, and within each type, a greater predominance of a few, dominant species. The tropics on the other hand offer a challenge of an altogether greater magnitude, with far greater numbers of landscapes, habitats, and species, distributed across a variety of stages of growth and succession, and with far more complex canopy structures (Nagendra 2001). Due in part to this challenging complexity, the use of remote sensing in the tropics has largely been limited to studies of deforestation (e.g., Geist and Lambin 2002), while hyperspectral and hyperspatial satellites have been insufficiently explored for ecological research in these areas (Sanchez-Azofeifa et al. 2003; Townsend et al. 2008).

A priority area of research for ecologists is the assessment and monitoring of biodiversity. This is especially essential in tropical habitats where much of the world's species diversity is concentrated (Nagendra and Gadgil 1999; Sanchez-Azofeifa et al. 2003; Loarie et al. 2007). With accelerated declines in tropical forest clearing and biodiversity across the world, there is an urgent need to identify the locations of biodiversity hotspots, map the distribution of biodiversity across different habitats and landscapes, and monitor rates of change over time. What is the potential of hyperspatial and hyperspectral data for this purpose?

Remote sensing has long been used to predict species rich sites based on both environmental heterogeneity as derived by spectral heterogeneity (Palmer et al. 2002; Foody and Cutler 2003; Rocchini et al. 2004; Hernández-Stefanoni and Dupny 2007) and Net Primary Productivity (NPP) as derived from vegetation indices such as NDVI (Fairbanks and McGwire 2004; Gillespie 2006). While some success has been achieved, obviously, no single factor such as landscape heterogeneity, or primary productivity, drives biodiversity patterns (Turner et al. 2003). Instead, species are clustered based on some exogenous factors, such as climate and soil type. Such clustering or autocorrelation of species distributions is often at broad scales, facilitating the use of medium-coarse resolution imagery for species diversity estimations (Dormann 2007). Other biotic and abiotic processes may however cause further structuring within smaller areas of relative environmental homogeneity, giving rise to small scale niche patterning, and fine scale variations in biodiversity (Legendre 1993; Wagner 2003).

In such cases, there is an apparent need for hyperspatial data. When medium pixel resolutions, a few tens of meters in size, are used for ecological studies, then a single pixel often encompasses a number of individual trees or plants, sometimes even crossing habitat boundaries (Small 2004). Thus each pixel corresponds to a mixed field signature averaged across multiple objects, leading to difficulties in identification of species identity, or the mapping of fine scale variations in biodiversity. Hyperspatial satellite imagery is potentially much better suited for biodiversity mapping with pixel sizes of the size of 5 m or less corresponding well to the size of individual tree crowns (Read et al. 2003; Wulder et al. 2004).

Figure 1 illustrates the potential of hyperspatial data for biodiversity studies. In this subtropical landscape in the Nepal Terai plains, the Rapti River separates the Chitwan National Park in the south from a mix of agricultural landscapes and human impacted forests to the north (Nagendra et al. 2008). Even a visual comparison of a Landsat ETM+ image of this landscape (Fig. 1a) with an IKONOS image of a nearby date (Fig. 1b) indicates that the IKONOS image is capable of detecting heterogeneity at a much finer scale that can be observed by the ETM+ image. The ecological impact of small streams and rivulets on biodiversity, and the human impact through roads, mud tracks and the nearby agricultural fields, which can be seen to an extent in the medium resolution Landsat image, is far more clearly discernible from the hyperspatial IKONOS image. A quantitative analysis of the data supports this (Nagendra, unpublished results).

For instance, studies in Australian woodlands (see e.g., Lassau et al. 2005) also indicate that hyperspatial multispectral imagery from a Compact Airborne Spectrographic Imager (CASI-2) enables the fine scale evaluation of habitat heterogeneity, and facilitates predictions of ant biodiversity. These investigators conclude that analysis at this level of detail would not have been possible using medium resolution imagery such as Landsat. Further, hyperspatial data may also prove useful in detecting species variability patterns at a local scale by further driving field sampling (Rocchini et al. 2005). Thus, while such data may not result in field surveys becoming obsolete, they can be very effectively used to develop more efficient, stratified field sampling design strategies.

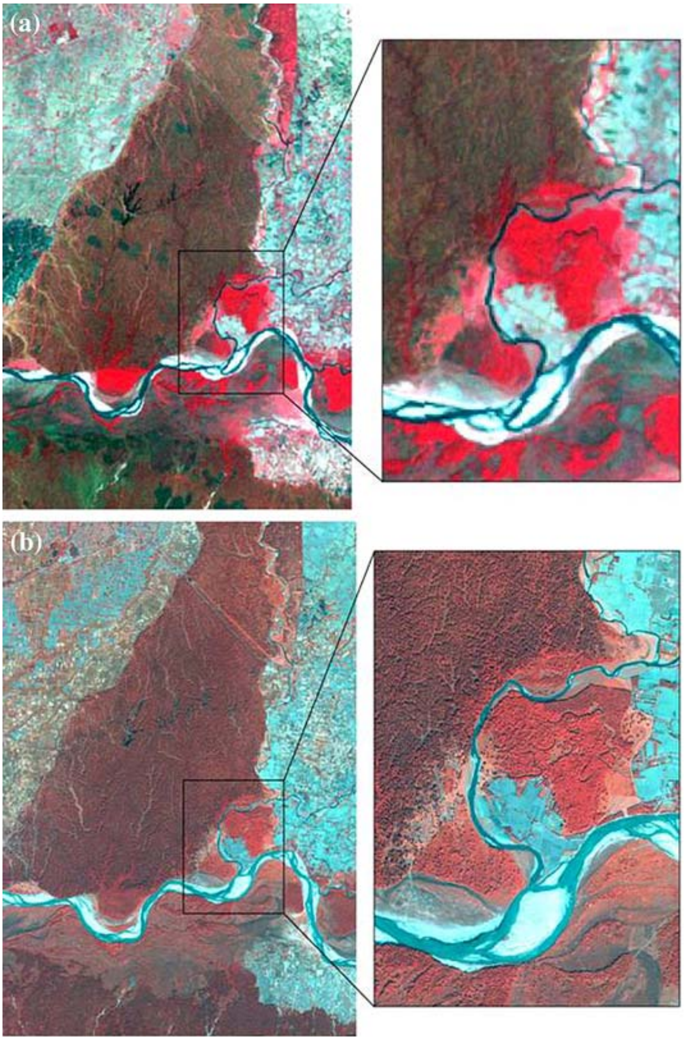

Fig. 1 A landscape in the Chitwan district, Nepal covered by (**a**) a Landsat ETM+ image of March 2000 and (**b**) an IKONOS image of October 2001

Yet, it is not always true that smaller pixel dimensions increase the accuracy of biodiversity assessment, particularly when the distribution of individual plants or trees constitute a mixture of spatial objects overlapping at multiple spatial scales (Nagendra 2001).When pixel dimensions shrink below the size of the object studied, to a point where individual pixels are smaller than the size of individual tree crowns, for instance, then there is a sudden increase in the variability of signatures of pixels that cover the same individual tree (Ricotta et al. 1999; Song and Woodcock 2002; Rocchini and Vannini 2008). This can happen, for instance, when some pixels cover a leaf in sunshine and others are located over dark gaps between leaves, or on the tree bark. In such situations, the high spatial resolution actually confounds the issue, and makes it harder to handle relatively simple tasks like delineating tree canopies, let alone assigning signatures to different species (Nagendra

2001; Wulder et al. 2004). This is corroborated by field experience. In an attempt to map the distribution of invasive trees in southern Florida, Fuller (2005) conclude that IKONOS imagery is not very useful for this task, due to the high levels of internal variability within tree canopies detected by this imagery, which make it difficult to delineate and classify individual tree crowns.

Hyperspectral data on the other hand, with their ability to collect information at a high spectral resolution using a series of contiguous spectral bands, each with a narrow spectral range, can be used to record information pertaining to a range of critical plant properties including leaf pigment, water content, and chemical composition (Curran 1989; Martin and Aber 1997; Townsend et al. 2008). Variability in hyperspectral information can be used to great effect for discriminating tree species in landscapes including tropical forests, despite the greater complexity of such environments (Cochrane 2000; Clark et al. 2005).

Hyperspectral data are capable of fairly accurate identification of different species (Nagendra 2001; Carlson et al. 2007). For instance, Thenkabail et al. (2004) demonstrated that Hyperion narrowband data led to land use classifications with an overall accuracy (up to 52%) higher compared with broadband sensors like IKONOS or Landsat ETM+ despite the lower spatial resolution being considered. In a study of lowland forests in Hawaii, Carlson et al. (2007) successfully used airborne hyperspectral imagery (AVIRIS) to predict species richness at a fairly fine scale of 0.1 ha. In the moist tropical forests of Costa Rica, Clark et al. (2005) found that at a fixed spatial scale, hyperspectral imagery like HYDICE performed significantly better than multispectral data like IKONOS, Landsat, and ASTER in discriminating tree species. In another study in Costa Rica, Kalacksa et al. (2007) found that the increased spectral resolution provided by Hyperion hyperspectral imagery is advantageous to the detection of forest biodiversity in a tropical dry forest landscape. Thus, in contrast to hyperspatial data which seem best suited to the accurate location of features such as tree canopies, hyperspectral data appear capable of significantly increasing the accuracy of identification of features such as species identity (Thenkabail et al. 2004).

There can be no doubt of the visual appeal of high resolution satellite images, which, through outlets such as Google Earth, have enabled in making detailed, fine scale colored images of large parts of the Earth easily available to the larger public. Yet, the scientific applicability of these images, particularly for ecological studies in the tropics, needs to be further investigated (Townsend et al. 2008). Many problems still persist. As stressed by Turner et al. (2003): ‘Remote sensing products should not be taken at face value. Atmospheric phenomena, mechanical problems with the sensor and numerous other effects might be distorting one’s view.’

However, efforts are being made to tackle technical issues related to calibration and geometric correction (Fraser et al. 2006), atmospheric correction (Wu et al. 2005), spectral enhancement (Ling et al. 2007) and spatial enhancement (Sohn and Dowman 2007) of high resolution satellite image data.

Despite the attractive possibilities that hyperspectral and hyperspatial imagery offer for biodiversity assessment, there have been few examinations of these data in the species rich tropics, compared to temperate areas (Townsend et al. 2008). There remains a glaring gap in the easy availability of such data across the world (Goetz 2007; Gillespie et al. 2008). This gap is especially prominent in tropical biodiversity hotspots, where the need for biodiversity assessment and monitoring is perhaps most critical (Kark et al. 2008). There are huge costs associated with developing and fabricating high spatial and spectral resolution sensors, and inevitable tradeoffs emerge between spectral and spatial resolution and temporal coverage, when one takes into account the immense sizes of the datasets involved, the time taken to download them, and the difficulties involved with data storage. Therefore, an

Table 1 Details of main satellite borne sensors currently available for biodiversity studies

Sensor	Satellite	Spatial grain (pixel size)	Spatial extent (swath width)	Spectral grain (number of bands)	Spectral grain (band width)	Spectral resolution	Coverage	Repeat period	Launch	Cost/sq km and availability
Hyperspectral										
CHRIS (Compact High Resolution Imaging Spectrometer)	PROBA (Project for On-Board Autonomy)	19–36 m	14 km	Upto 62, programmable	1–12 nm	Upto 410–1,050 nm, programmable	On demand	On demand	October 2001	Access provided free of charge for researchers and projects approved by the European Space Agency http://earth.esa.int
Hyperion	EO-1 (Earth Observing-1)	10 m PAN, 30 m all other bands	7.7 km	220	10 nm	356–2,578 nm	On demand	Potentially schedulable up to 7 days	November 2002	USD 250/scene or 0.77/km^2, for level 1 radiometrically corrected data (from USGS—United States Geological Service) http://edc.usgs.gov
GLI (Global Imager)	ADEOS-II (Advanced Earth Observing Satellite-II)	250 m—6 bands corresponding to Landsat, 1 km—all other bands	1,600 km	36	12–2,985 nm	380–12,000 nm	Global	4 days	December 2002	Unknown
MERIS (Medium Resolution Imaging Spectrometer)	ENVISAT	250 m–1 km	1,150 km	15	2.5–12.5 nm, programmable	390–1,040 nm	Global	3 days	February 2002	Access provided free of charge for researchers and projects approved by the European Space Agency http://envisat.esa.int
MODIS (Moderate Resolution Imaging Spectrometer)	TERRA	250 m VNIR, 500 m VNIR-SWIR, 1 km TIR	2,330 km	36	10–15 nm VNIR-SWIR	405–14,385 nm	Global	1–2 days	December 1999	Available free of charge from USGS http://edc.usgs.gov
Hyperspatial										
IKONOS	IKONOS	1 m PAN, 4 m MSS	11.3 km	5	71–96 nm	445–853 nm	On demand	Potentially schedulable upto 3 days	September 1999	USD 7/km^2 for archived GEO data, 4 m MSS (from GeoEye) http://www.geoeye.com

Table 1 continued

Sensor	Satellite	Spatial grain (pixel size)	Spatial extent (swath width)	Spectral grain (number of bands)	Spectral grain (band width)	Spectral resolution	Coverage	Repeat period	Launch	Cost/sq km and availability
Orbview-3	Orbview-3	1 m PAN, 4 m MSS	8 km	5	70–140 nm VNIR	450–900 nm	On demand	Potentially schedulable upto 3 days	June 2003 (unavail able since March 2007)	USD 5/km^2 for archived BASIC enhanced data, 4 m MSS (available from GeoEye) http://www.geo-eye.com
BGIS-2000 (Ball's Global Imaging System-2000)	Quickbird	0.61 PAN, 2.44 m MSS	16.5 km	5	70–140 nm VNIR	450–900 nm	On demand	Potentially schedulable upto 1–4 days	October 2001	USD 16/km^2 for archived standard MSS data (available from DigitalGlobe) http://www.digital-globe.com
Other										
Advanced Land Imager (ALI)	EO-1	10 m PAN, 30 m MSS	37 km	10	20–270 nm	400–2,500 nm	On demand		November 2002	USD 250/scene or 0.16/km^2, for level 1 radiometrically corrected data (from USGS—United States Geological Service) http://edc.usgs.gov
ASTER (Advanced Spaceborne Thermal Emission and Reflectance)	TERRA	15 m VNIR, 30 m SWIR, 90 m TIR	60 km	14	40–100 nm	520–1,165 nm	Global	16 days, potentially schedulable upto 5 days	December 1999	USD 80/scene or 0.02/km^2, for level 1A reconstructed unprocessed instrument data (from USGS) http://edc.usgs.gov
AVNIR-2 (Advanced Visible and Near Infrared Radiometer Type 2)	ALOS (Advanced Land Observing Satellite)	10 m	70 km	4	80–130 nm	420–890 nm			January 2006	AUD330 (USD320)/scene, or 0.07/km^2 (from JAXA — Japanese Aerospace Exploration Agency, via international distributors such as ACRES—Australian Centre for Remote Sensing) http://www.eorc.jaxa.jp; http://www.ga.gov.au/acres/

Table 1 continued

Sensor	Satellite	Spatial grain (pixel size)	Spatial extent (swath width)	Spectral grain (number of bands)	Spectral grain (band width)	Spectral resolution	Coverage	Repeat period	Launch	Cost/sq km and availability
Landsat TM (Thematic Mapper)	Landsat 4, 5	30 m MSS, 120 m TIR	185 km	7	60–270 nm MSS	450–2,350 nm MSS, 10, 400–12, 500 TIR	Global	16 days	July 1982	Selected archive data available free of charge from USGS or the Global Land Cover Facility at University of Maryland http://glcf.umiacs.umd.edu; all archive data to be available free of charge from December 2008 (Landsat 5), and April 2009 (Landsat 4), from USGS http://landsat.usgs.gov/
Landsat ETM + (Enhanced Thematic Mapper)	Landsat 7	15 m PAN, 30 m MSS, 60 m TIR	185 km	8	60–270 nm MSS	450–2350 nm, 10,400–12,500 TIR	Global	16 days	April 1999 (suspended since May 2003)	Selected archive data available free of charge from USGS or the Global Land Cover Facility at University of Maryland http://glcf.umiacs.umd.edu; all archive data to be available free of charge from September 2008 from USGS http://landsat.usgs.gov/
HRVIR (High Resolution Visible and Infra Red)	SPOT-5 (Satellite Pour l'Observation de la Terre-5)	2.5–5 m PAN, 10 m MSS, 20 m SWIR	60 km	5	70–230 nm	500–1,750 nm	Global	26 days	May 2002	USD 3375/scene, or 0.94/km^2, for level 1A, 1B and 2A data, from SPOT Image Corporation http://www.spot.com
LISS 3 (Linear Imaging Self-Scanning Sensor –3)	IRS P6 (Indian Remote Sensing satellite system P 6), also known as ResourceSat-1	23.5 m	140 km	4	60–150 nm	520–1700 nm	Selective, based on locations of receiving stations	24 days	October 2003	USD 285/scene (INR 12000), or 0.07/km^2, for standard full scene MSS data, from National Remote Sensing Agency (NRSA) http://www.nrsa.gov.in

Table 1 continued

Sensor	Satellite	Spatial grain (pixel size)	Spatial extent (swath width)	Spectral grain (number of bands)	Spectral grain (band width)	Spectral resolution	Coverage	Repeat period	Launch	Cost/sq km and availability
LISS 4 (Linear Imaging Self-Scanning Sensor –4)	IRS P6/Resource-Sat 1	5.8 m	70 km PAN, 23.9 km MSS	3	60–90 nm	520–860 nm	Selective, based on locations of receiving stations	5 days	October 2003	USD 360/scene (INR 15000), or 0.001/km^2, for standard full scene data, from NRSA http://www.nrsa.gov.in
AWiFS (Advanced Wide Field Sensor)	IRS P6/Resource-Sat -1	56 m	740 km	4	60–150 nm	520–1,700 nm	Selective, based on locations of receiving stations	5 days	October 2003	USD 595/scene (INR 25000), or 0.01/km^2, for standard full scene MSS data, from NRSA http://www.nrsa.gov.in
AVHRR (Advanced Very High Resolution Radiometer)	NOAA (National Oceanic and Atmospheric Administration)	1.1 km	6,400 km	6	100–1,000 nm	580–12,500 nm	Global	Twice daily	June 1979	USD 190/scene or approximately 1.4×10^{-5}/km^2, for georegistered level 1b data (from USGS—United States Geological Service)—derived coarse scale products available free of charge http://edc.usgs.gov
VEG2 (Vegetation 2)	SPOT-5	1 km	2,250 km	4	70–170 nm	430–1,750 nm		26 days	May 2002	USD 180/million km^2, for NDVI data, from SPOT Image Corporation http://www.spot.com. Selected derived archive data available free of charge, from SPOT Vegetation Programe http://www.spot-vegetation.com

PAN, Panchromatic; VNIR, visible to near infra red; SWIR, short wave infra red; TIR, thermal infra red; MSS, multispectral increase in the resolution of one attribute, such as increasing spectral resolution, often leads to a sacrifice of other attributes, such as temporal resolution or spatial coverage. The increased pricing of such imagery also puts it out of the reach of many ecologists (Gillespie et al. 2008)—especially those located in developing countries where the need is perhaps greatest.

Table 1 describes the spatial and spectral resolution, the geographic coverage, temporal frequency and cost of the satellite sensors and platforms routinely used for biodiversity studies and vegetation mapping today. While hyperspectral data are generated at medium spatial resolutions of 20–30 m at best, hyperspatial data are usually multispectral, spanning 4–5 bands. The increased cost of these data limits their use in scientific studies (Gillespie et al. 2008). Further, unlike older satellite programs such as Landsat, hyperspectral and hyperspatial sensors, whether airborne or satellite borne, do not routinely cover all areas of the globe at repeated intervals of time (Loarie et al. 2007). Instead, they collect images when commissioned. Thus, obtaining archival data for a specific area and time period is a matter of chance, even if one has the money available for such research. Given the relatively recent arrival of these instruments, and their limited geographic spread, their utility will only be realized to the full when they will be coupled with existing large scale monitoring systems that currently utilize moderate resolution multispectral data like SPOT, ASTER, and Landsat TM/ETM+ to great effect (Duro et al. 2007).

Finally, some countries also impose restrictions on the availability of hyperspatial data, due to concerns about security. Thus, while there is a real need for more studies that utilize high resolution satellite imagery for biodiversity assessment in the tropics, such research will only receive its final impetus when these data will be available across all parts of the world with the same temporal frequency, at reasonable prices, and without imposing restrictions on their availability for research.

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