Figure 3.1. Tree crown map produced manually from a high-resolution aerial image of Barro Colorado Island (Panama). Mapped species: *Jacaranda copaia* (A), *Attalea butyraceae* (B), *Tabebuia guayacan = Handroanthus guayacan* (C) and *Astrocaryum standleyanum* (D). Photo by Marcos Guerra

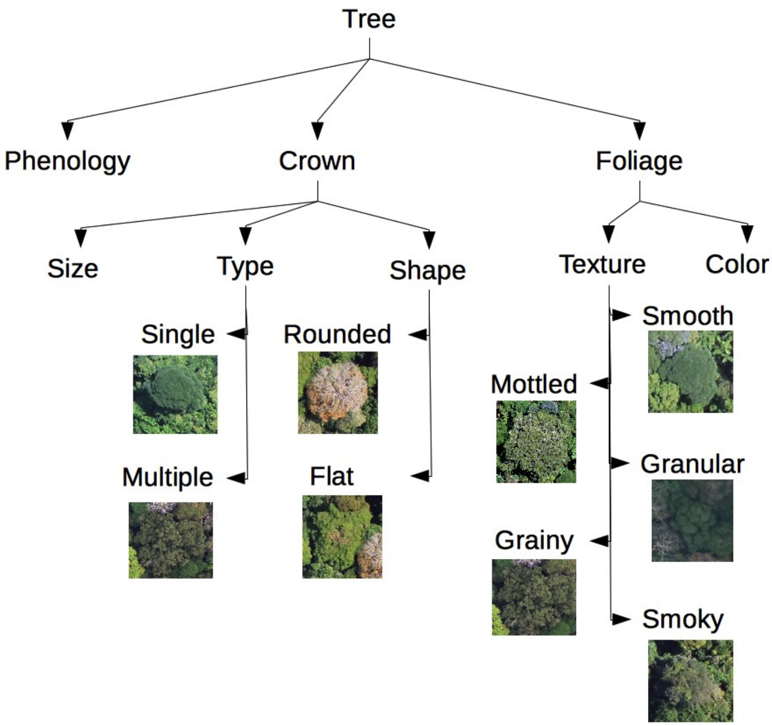

Figure 3.2. Criteria used for manual identification of tree crowns of different species from high-resolution aerial images of Barro Colorado Island (Panama).

Chapter 3

APPLICATIONS OF REMOTE SENSING FOR TROPICAL FOREST RESTORATION: CHALLENGES AND OPPORTUNITIES

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ABSTRACT

The tremendous physical and material efforts required to accurately assess forest degradation and to plan and monitor vegetation recovery using conventional ground surveys, often limit the success of tropical forest restoration projects. Remote sensing has become an important tool for biodiversity monitoring, ecological studies and climate change assessments. It has enormous potential to automate assessments of forest degradation and to standardize and increase accuracy of information at multiple temporal and spatial scales throughout the forest restoration process. It also drastically reduces labour costs involved in vegetation surveys. Remote sensing data vary in their complexity from two-dimensional RGB images, collected from analogue or digital cameras, to three dimensional hyperspectral cubes, covering hundreds of bands. Here we summarize current applications of available remote sensing methods for various forest restoration tasks and discuss the challenges and opportunities of using remote sensing in automated tropical forest restoration.

Key words: remote sensing, GIS, aerial images, hyperspectral data, lidar, multispectral data, satellite data, tropical tree species identification.

INTRODUCTION

Structurally complex and carbon-rich, tropical moist and wet forests (hereafter, Humid Tropical Forests, HTF) are some of the most biologically diverse ecosystems on Earth. They exhibit high species richness but, at least in the Neotropics, most species are quite rare. TER STEEGE et al. (2013) estimate that 1.4 % of species account for about half of all individuals. As plants are primary producers and dominate landscapes, their roles are always key to habitats. However, tropical forest

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destruction is on-going. Based on Landsat data, current rates of tropical deforestation globally are estimated to be 7.6 million ha per year (ACHARD et al. 2014). Such estimates vary for several reasons, the most important of which are the definition of deforestation (e.g. degree, change or identity of tree canopy cover) and the counting method (e.g. satellite data, field-based extrapolations etc.).

Identifying and locating specific trees, or group of trees, is fundamental to i) assessments of forest biodiversity, ii) increasing our understanding of ecosystem functioning and iii) reforestation methods that prescribe the use of multiple native species to re-establish forest structure (e.g. the framework species method (ELLIOTT et al., 2013). Traditionally, identification and mapping of HTF species has been done using labour-intensive, ground-based surveys or by interpreting large-scale (> 1:4000) aerial photographs (ZHANG et al. 2006). Both methods are costly and time-consuming. However, with the advent of small unmanned aerial vehicles (UAVs), aerial photography has become both more cost-effective and rapid. In addition, researchers are now also turning to other remote sensing methods (Table 3.1) to assess a host of vegetation parameters, such as spatial structure, complexity, dynamics and species distribution.

Aerial digital photography

Maps of species distributions are fundamental to the study of tropical forest ecology, allowing us to increase our understanding of population and community dynamics, and they form the basis of ecological monitoring and management plans (MYERS, 1982; CONDIT et al., 2000; JANSEN et al., 2008; MORGAN et al., 2010).

High-resolution aerial photography is a relatively inexpensive solution for the identification and mapping of species at large scales (Fig. 3.1). It has been applied to the identification of tree species in temperate forest with good results (PAINE & KISER, 2003). In the case of the highly-diverse HTFs, this technique has been used in very few cases because of the difficulty associated with recognizing species from crowns, often intermixed, and has mostly been limited to mapping a single or few, often distinctive, species (Fig. 3.1).

SAYN-WITTGENSTEN (1978) attempted to identify timber tree species in the tropical forests of Surinam and found the approach promising, but highlighted the need for criteria to identify species. Later, CLEMENT & GUELLEC (1974) and VOOREN & OFFERMANS (1985) working in Gabon and south-eastern Ivory Coast, were able to map one focal species in each ecosystem. MYERS (1982) successfully identified 24 tree species with 75% accuracy in the forests of Queensland (Australia).

Table 3.1. Current and planned remote sensing products and platforms with specifications. Number of signs increases with increasing costs ($) or data processing/storage (*) needed.

Platform	Sensor	Resolution (m)	Extent	Frequency (days)	Spectral regions (bands)	Tree species identification	Other applications	Processing/ Storage	Costs
Satellite	Ikonos	1-4	>1000 km²	3-4	up to 4	Only very conspicuous (color, size) tree species	Tree crown density and size Forest condition	**	$$$
	Quickbird	0.65-2.62						**	$$$
	WorldView2	0.65-2						**	$$$
	GeoEye1	0.65-2						**	$$$
	Landsat 7	15-60		15	8		NDVI Forest type classification	**	$$
	MODIS	250-1000		1-2	36	Forest type classification	Tree crown density and size Forest condition	**	$
	Hyperion EO-1	30		15	220		Spectral signature, functional types	***	$$
	EnMAP	30		4	400		Planned for 2018		
	PRISMA	20-30		1-2	10		Planned for 2015		
	HyspIRI			5	10		Planned for 2022		
Airborne	Hyperspectral (AVIRIS or APEX)	2-20	<1000 km²	Planned	224	Identification by spectral signature	Biomass Plant functional traits Invasive species ID, location NDVI	***	$$$$$
	LiDAR	0.15			3D structure	Provides data on height and form, used in combination with other imagery for identification	Canopy height Biomass Digital elevation model Tree crown structure	***	$$$$$
	Aerial images	1-10			up to 3	Identification by tree (mostly crown) morphology	Tree crown size and density Forest status	**	$$

Trichon and colleagues (González-Orozco et al., 2010; Trichon, 2001; Trichon & Julien, 2006) developed a multi-criteria hierarchical system to describe crown typology from aerial photographs; it comprised seven discrete variables: crown size, phenology, crown type, crown shape, foliage texture and colour (Fig. 3.2). This crown identification key was developed at a study site having precise ground coordinates of previously identified (known) species (Garzon-Lopez et al., 2013). The crowns, visible in the aerial images were carefully matched with their ground locations and, in this way, the species were mapped.

The aforementioned method relies on manual interpretation (delineation) of crowns by trained experts, people who are often in short supply and expensive to employ. Consequently, automated interpretation has been attempted (just as for other forms of remote sensing) using modern methods of digital image analysis, based on pixel- or object-based classifications (by a process of segmentation) (Morgan et al., 2010). In fact, the steps involved, such as associating known crowns with location, using a combination of criteria (involving sun-lit pixels and e.g., image texture and shape recognition) are roughly similar in manual and automated interpretation of tree crowns.

Some of the applications of aerial tree crown interpretation include assessment of tree aging (Vooren & Offermans, 1985) and crown dynamics (Herwitz et al., 1998); monitoring of forest degradation or fires (Paneque-Gálvez et al., 2014); locating fruiting events and measuring their intensity (Jansen et al., 2008; Van Andel et al. 2015); and the development of large-scale species distribution maps, to study plant-habitat associations (Garzon-Lopez et al., 2014), animal behaviour (Brown et al., 2014) and animal movement patterns (Caillaud et al., 2010; Van Andel et al., 2015).

The choice of a platform, used to carry the camera, depends on the extent of the study area and platform availability, and has a significant effect on determining project costs. Platforms have typically been (in order of increasing cost) ultra-light aircraft, small airplanes and helicopters. With the advent of inexpensive off-the-shelf and do-it-yourself UAVs, user-friendly, readily mobilized platforms are now available, allowing exceptionally cost-effective forest mapping. Flight patterns for UAVs, carrying small-format cameras, can be pre-programmed to capture aerial photographs (images) with a high degree of overlap for later mosaicking. Furthermore, using off-the-shelf automated photogrammetric software packages, such images can be used to generate digital elevation models (DEMs). Thus, the canopy can be mapped and a digital terrain model (DTM) produced at resolutions, set by the user. Additionally, UAV missions may be run and operated by trained local people, so that images may be obtained in remote areas without entailing numerous lengthy field trips by foresters or other expensive specialists. Depending upon regional expertise, aim of the aerial survey and computer processing power available, crown identification can be done i) manually, ii) using a combination of experts and trained volunteers (GONZÁLEZ-OROZCO et al., 2010) or iii) by automated digital image analysis, developed and run by experts.

In conclusion, aerial images can be used to support various forest restoration tasks (Table 3.2), from rapid pre-intervention site assessments for determining baseline levels of degradation, and identification (and location) of trees that can serve as seed sources, to monitoring of the progress of restoration following interventions.

Light Detection and Ranging (Lidar)

Lidar technology measures the travel time of a laser pulse from an emitter to a target and back to a detector (up to 400,000 pulses of light per second) and derives the distance to the target from the return time. When using a lidar unit mounted on an aerial platform (AP) to survey vegetation, pulses are reflected from the canopy (first return) and the ground (last return). Canopy height is calculated by subtracting the first from the last return time, taking into account AP position (altitude, yaw, roll and pitch). Using this approach, the instrument collects three-dimensional data in large volumes, at high density and with unprecedented precision.

The instrument consists of a laser emitter, a global positioning system (GPS) receiver, providing geographic location, and an inertial measurement unit (IMU), which records AP position. Lidar systems are categorized according to the type of data they record, as either discrete return or full waveform systems. Discrete return systems can be programmed to record (i) only the first return, (ii) the first and last return; or (iii) multiple returns; full waveform systems transmit continuous signals and the distance is measured based on changes in laser intensity.

Data resolution is dependent on the number of pulses per unit area and the size of the pulse (area of the footprint), which is in turn determine by altitude. For the discrete system, the footprint varies between 0.2 and 0.9 meters, while in full waveform systems it varies between 8 to 70 meters (LIM et al., 2003). Full waveform systems are gaining popularity because they can capture reflections of the emitted laser pulse in greater detail than discrete ones.

Aerial lidar sensors deliver a 3D point cloud of the forest that can then be processed to i) a digital surface model (DSM) that includes all the objects on the ground (e.g. trees, buildings, etc.), ii) a digital terrain model (DTM) that provides a view of the bare ground (without any objects) and iii) a set of very precise canopy metrics like the canopy height model (CHM), a canopy density map and the average, maximum and minimum canopy height. These forest height metrics can be related to observed above ground biomass (AGB) estimated by field measures and allometric relationships in inventory plots. Operational costs often limit the spatial extent of lidar-derived AGB estimates, but accurate estimates are vital if forest restoration projects are to be funded by REDD+ (Reducing Emissions from Deforestation and Forest Degradation) or other carbon-trading systems. In combination with other remote sensing approaches, local AGB maps may be scaled up to cover larger areas (LAURIN et al., 2014).

Up-scaling an aligned lidar sampling of Panama using Landsat satellite data of topography, precipitation and vegetation cover, ASNER et al. (2013) modelled carbon stocks at a 1 ha spatial resolution to produce a carbon map of Panama. They found that lidar estimated carbon stocks were similar to those estimated from inventory plots and concluded that lidar collected measurements can replace laborious field-derived ones, although validation plots "remain highly valuable for increasing accuracy and transparency" (ASNER et al., 2013). Using a light airplane equipped with a small footprint lidar, hyperspectral sensor and a digital camera for aerial photographs, LAURIN et al. (2014) estimated AGB of forest in the Gola Rainforest National Park in Sierra Leone. These workers found that integration of the hyperspectral data improved the lidar-based model and cautioned that high quality field data is essential for lidar-based AGB estimates, particularly if the estimates from airborne lidar are to be used to upscale the field-measurements.

Even though lidar data acquisition and processing can be very expensive (HUMMEL et al., 2011), there is an economy-of-scale effect whereby the larger the study area, the greater the lidar data acquisition costs are reduced, in the case of Panama to about $1.00 USD per hectare (ASNER et al., 2013). While, ground field plots are expensive to establish and maintain, costing on the order of (~$2000 to $5000 USD per ha) for the same country (ASNER et al., 2013).

Notwithstanding, on the whole, prices for aerial lidar measurements are decreasing as lidar sensors become smaller, lighter and cheaper, as computer processing power and data transfer rates increase. Further, lidar efficacy is improved when used in combination with other technologies. For example, in automated aerial tree mapping, both lidar and hyperspectral data can be collected simultaneously (BALDECK et al., 2015). Lidar data are used to derive tree height measurements and the 3D structure of the vegetation and are also used for accurate orthorectification of the spectral data. Medium-priced systems that combine very high-resolution photography with lidar are also available. In Cambodia, SINGH et al., (2015) used such a system for tree mapping in HTF, where ground field data collection was not possible due to the presence of landmines.

Imaging spectroscopy (spectroradiometry)

Spectroscopy is the analysis of light, emitted by or reflected from matter and its variation in energy at different wavelengths. In reflected-light spectroscopy, the basic property of interest is spectral reflectance: the ratio of reflected energy to incident energy, as a function of wavelength. For most materials, reflectance varies with wavelength, because energy at different wavelengths is differentially scattered or absorbed. These variations in reflectance are evident, when spectral reflectance curves for different materials, in our case vegetation, are compared. Pronounced downward deflections of the curves indicate wavelengths that a material selectively absorbs and are termed "absorption bands". Overall spectral curve shape, and absorption bands' strength and position of absorption bands can be used to identify, and discriminate among, different materials. Minerals, which are comparatively structurally simple and stable, can be classified in this manner and a library of reflectance spectra exists. Vegetations and their component plants are dynamic and interpretation of their reflectance spectra is more complex. In a general manner, spectral reflectance curves of healthy plants have characteristic shapes, related to plant attributes. In the visual spectrum (VIS), curve shape is governed by plant pigment (e.g. chlorophylls, carotenes, anthocyanin, betalains) absorption. Chlorophylls absorb blue and red wavelengths more strongly than green, which is largely reflected (hence plants appear green to our eyes). This appears on reflectance curves as a characteristic peak within the green wavelength range. Reflectance rises sharply to values of about 40 – 50% for most plants across the boundary between the red and near-infrared (NIR) wavelengths (680 – 750 nm), and is known as the "red edge" effect. This high NIR is related to several factors such as chlorophyll concentration, species morphology (organization and construction), developmental stage and leaf water content (GHIYAMAT & SHAFRI, 2010). Otherwise, in the NIR, most of the remaining energy is transmitted and can interact with other lower leaves. Beyond 1.3 µm, reflectance decreases with increasing wavelength, except for two conspicuous water absorption bands, near 1.4 and 1.9 µm (SOLDOVIERI et al., 2011). Imaging spectroscopy is typically studied between 400 and 2500 nm, that is from the VIS 400-700 nm, through the NIR 701 – 1400 nm and Short-Wave InfraRed 1 (SWIR 1) 1401 - 1900, to the Short-Wave InfraRed 2 (SWIR2) 1901 – 2500 nm.

Although terminology is imprecise, a general distinction is made between multispectral and hyperspectral sensors. Multispectral remote sensors (such as the Landsat Thematic Mapper and SPOT XS) produce images having few relatively broad wavelength bands, whereas hyperspectral remote sensors collect image data simultaneously in dozens or hundreds of narrow, adjacent spectral bands.

Hyperspectral measurements make it possible to produce a continuous spectrum for each image cell or pixel. These data sets are generally composed of about 100 to 200 spectral bands of relatively narrow bandwidths (5-10 nm), whereas multispectral data sets are usually composed of about 5 to 10 bands of relatively large bandwidths (70-400 nm). Hyperspectral imagery measurements can be represented as a data cube, with spatial information represented by the X-Y plane and spectral information represented in the Z-direction (Fig. 3.4). Multispectral sensors, principally deployed on satellites, are useful in detecting vegetation types but have limited capacity to detect tree species (especially tropical ones), because they lack the fine spectral resolution provided by hyperspectral sensors (CASTRO-ESAU & KALACSKA, 2008). Recall that resolution has two components, a spatial one and a spectral one. In hyperspectral imagery, reflectance spectra are continuous and pixel resolution is in the order of 15 cm to 1 m, depending on the sensor and its distance from the target.

The potential uses of hyperspectral imagery (in the lab or airborne, often in combination with other remote sensing techniques) for monitoring HTF composition, cover and function are numerous and the subject is vast. Hyperspectral data (spectral signatures) are essentially a reflection of interactions between light and physical and chemical properties, be they cells, tissues, organs (often leaves, known as leaf optical properties), individuals (often crowns), populations, communities, ecosystems or other higher-level groups. Hence, some of the common data uses are for studies of:

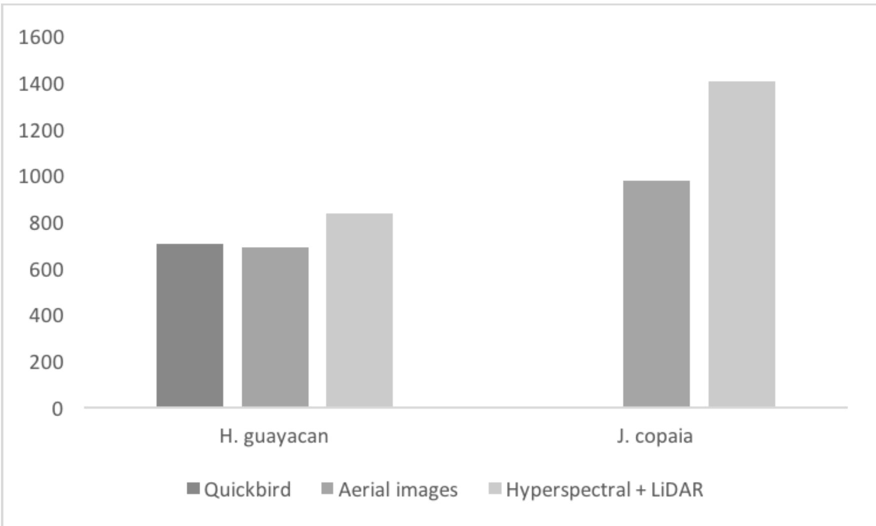
1. leaf chemistry, structure and function (e.g., rates of photosynthesis);
2. life forms (e.g., liana or tree, see KALACSKA et al., 2007);
3. phenology and
4. detection and mapping of species.

Moreover, combinations and derivatives of the elemental data are the building blocks for detection/analysis of plant traits and growth forms (HOMOLOVÀ et al., 2013), and vegetation indices (LAURIN et al., 2014). Currently the use of hyperspectral sensors is largely limited by the costs of the sensor as well as associated data acquisition and processing, but this is rapidly changing with the development of new technologies, such as compact light-weight sensors and open source processing software.

APPLICATIONS OF REMOTE SENSING TO TROPICAL FOREST RESTORATION

Remote sensing technologies have a wide range of applications in forest restoration, from the identification and assessment of sites to be restored, identification of tree species, location of "mother" trees as seed sources and the necessary frequent monitoring of the restoration process. Multiple technologies can be combined to increase the efficacy of restoration, while minimizing limiting factors to restoration such as costs, labour and time. They also enable restoration to be carried out on remote, inhospitable terrain, where it would otherwise be impractical because of the aforementioned limitations.

Figure 3.3. Number of tree individuals, in the tropical forest of Barro Colorado Island (Panama), identified using satellite (Quickbird), aerial and hyperspectral combined with lidar images, respectively (adapted from Baldeck et al., 2015).



BALDECK et al. (2015) recently presented an automated method to identify tree species in HTF using combined hyperspectral imagery and lidar data. These authors compared their results with two previous attempts made at the same study site using satellite-based Quickbird images and automated crown delineation methods (*Handroanthus guayacan* and *Jacaranda copaia*), and manually delineated crowns of high-resolution aerial images (*J. copaia*). They found that hyperspectral + lidar data resulted in better species detection, due to higher resolution of forest structure (Fig. 3.3), however, their method is considerably costlier.

Remote sensing method of choice will differ depending on goals, budget and the landscape. For example, initial assessment of the landscape might require information at low resolution over a large area, for which the best approach might be free, readily-available, on-line, pre-processed satellite images. However, if the aim is to assess forest structure and locate and identify seed trees, then the best option might be aerial images (approx. $0.2 USD per hectare), or if it is to characterize (and monitor changes in) forest structure (e.g. canopy height, AGB, functional diversity) or develop a high-resolution DEM the best results will be obtained using hyperspectral +/- lidar sensors (approx. $0.5 USD per hectare). The selection will also depend on the characteristics of the focal species (Fig. 3.2) and the selected area (Table 3.2).

DEVELOPING PRACTICAL APPLICATIONS TO AUTOMATE FOREST RESTORATION

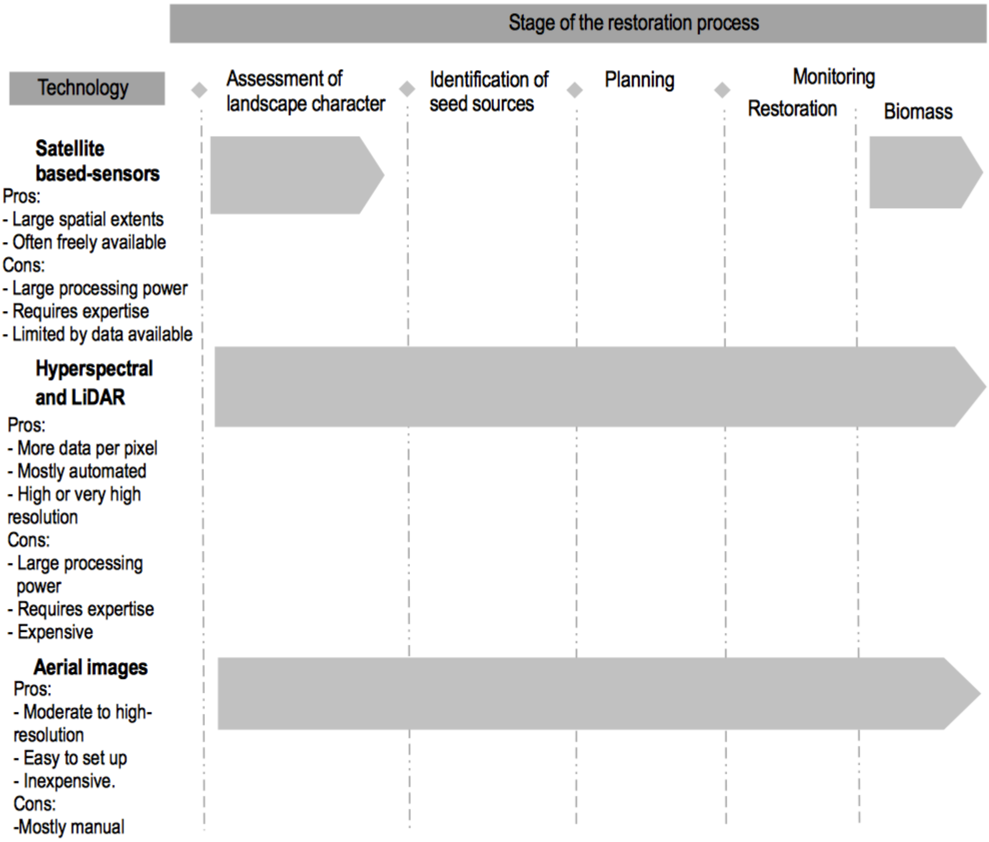
We turn our attention now to the priorities for research and development that arose out of the brainstorming sessions of the 2015 workshop on Automated Forest Restoration (AFR) Chiang Mai, Thailand – how to apply the imaging technologies described above to develop robust, cost-effective and automated methods for forest restoration.

Firstly, it must be emphasized that basic knowledge about how to restore local forest ecosystems, by conventional means, must already exist, before technology can be used to make the tasks of forest restoration easier. Restoration sites should be selected on the basis of sound social and ecological criteria, through consultation with all stakeholders; a process for which there is no technological substitute. A list of indigenous forest tree species known to be most suited to the conditions at the restoration site is also an essential minimum pre-requisite.

The next step is to map the selected restoration site, locate the nearest surviving remnant of the reference (or target) forest ecosystem (which will serve as the goal of restoration) and locate individual seed trees of the selected, suitable, species within it.

This can be done in several ways and at multiple scales (it is advisable to use more than one). At large scales, freely-available satellite images can be used. At local scales, numerous points can be verified by using hand-held GPS receivers, or UAV-mounted GPS receivers and cameras (as described above). The latter method could also generate DEMs and CHMs.

Table 3.2. Applications of remote sensing to various stages of tropical forest restoration.



Another early important step can be to develop databases that combine information gleaned from previous experience and to fill knowledge gaps. The databases should cover species location, phenology (flowering, fruiting, leafing months), reproductive biology, seed dispersal method, seed germination requirements and seedling biology. The database should be linked to an image library. This library should contain different views of trees (e.g. crowns, trunk) and various organs, as well as of seedlings and treelets; priority should be given to framework species. UAV-mounted cameras may be used to obtain some of these images. The image library would form the basis for a species-identification tool, similar in concept to Pl@ntNet (JOLY et al., 2014) (see Chapter 11).

After these steps, if higher resolution is required then hyperspectral and lidar sensors may be employed. As these sensors are becoming smaller, lighter and less expensive, by the time the databases and image libraries near completion, complementary new technologies (such as the promising hyperspectral camera based on CMOS technology) and user-friendly methods are likely to have become widely available.

Currently, challenges to acquiring aerial images from UAVs, and/or to data acquisition from UAVs, airplanes and satellites include:

1. Most hyperspectral and lidar sensors are expensive and heavy (> 4 kg). Although changing, this remains an important limitation. Moderately priced UAVs have a maximum payload capacity of ca. 2-4 kg and limited flight durations (30-60 mins), depending on weight.
2. High dimensionality of the data makes both lidar and spectroscopic (especially hyperspectral) imagery hard to transfer and store. High-performance computers, having large storage capacities, are necessary. Moreover, modelling algorithms are complex and require long computational times;
3. Most HTF tree species are very rare, even over large spatial scales.
4. Airborne and satellite spectroscopic sensors detect over-storey trees. Understory trees cannot be detected by these means.
5. When using lidar, dense canopy cover limits the number of discrete pulse returns from the ground, making it difficult to produce well-resolved DTMs.
6. Weather conditions affect remote sensor outputs. Clouds can block satellite images. Flights must be conducted on clear days or below clouds and in little to no wind. High humidity can also affect results.

Although numerous challenges remain to be surmounted before many recently described methods of remote sensing can be practically applied to the automating of tropical forest restoration, the technologies outlined in this article also open up many new opportunities. Using inexpensive digital cameras mounted on cheap off-the-shelf or do-it-yourself UAVs (such as the Flone described in Chapter 7) is an excellent starting point for providing basic information, for planning and implementing successful restoration projects, as well as providing a means of monitoring on-going projects.

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KEY TO ABBREVIATIONS

AFR = Automated Forest Restoration
AGB = Above Ground Biomass
AP = Aerial Platform
CHM = Canopy Height Model
DEM = Digital Elevation Model
DSM = Digital Surface Model
DTM = Digital Terrain Model
HTF = Humid Tropical Forest
Lidar = Light Detection and Ranging
NIR = Near InfraRed
NDVI = Normalized Difference Vegetation Index
SWIR = Short Wave InfraRed
UAV = Unmanned Aerial Vehicle
VIS = Visual (spectrum)

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Figure 3.4. a. The Hyperspectral image cube is built as the sensor passes over the ground. b. The hyperspectral curves are generated from the reflectance values extracted from a specific point/area/pixel (x, y) at each wavelength.