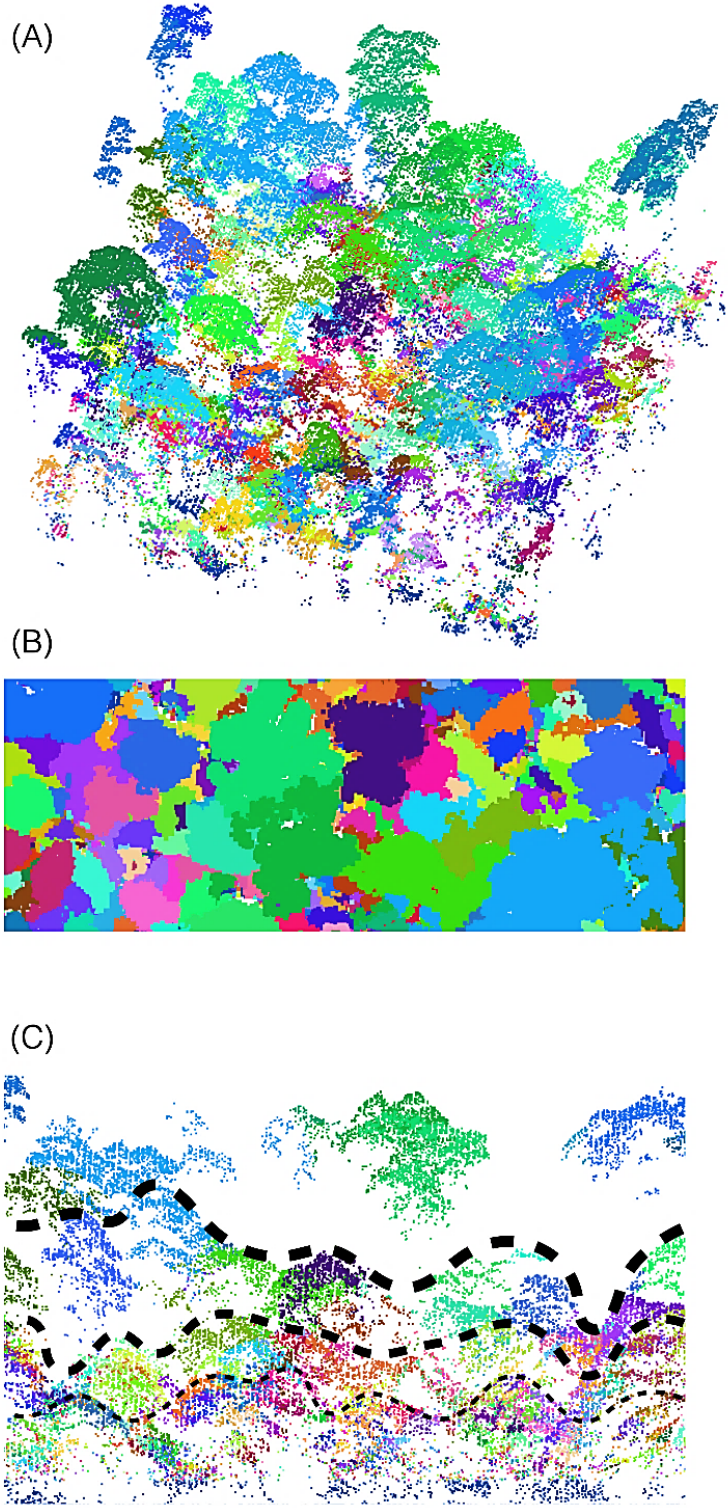

Figure 12.1

(A) A lidar point cloud from a manned aerial survey at Sepilok, Malaysia. Algorithmic (DBSCAN) segmentation was used to assign a different colour to each tree crown (oblique view).

(B) A horizontal projection of the canopy.

(C) A vertical cross-section of the canopy, with segmentation of canopy layers, shown as dashed curves.

Chapter 12

AUTOMATED VEGETATION MONITORING FOR FOREST RESTORATION

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ABSTRACT

We discuss the potential of automating vegetation monitoring, to aid forest restoration. We propose that automated monitoring focuses on estimating forest biomass and tree diversity, because these are relevant to many ecosystem services, and they can be assessed with existing automated technologies, to some extent. We discuss the importance of setting baselines and realistic goals that take into account site history and landscape context. We review relevant technologies, including unmanned aerial vehicles (UAVs), lidar, multispectral and hyperspectral sensors, visible-light cameras and data-processing software. We discuss advantages and disadvantages of below- versus above-canopy surveys. We identify technological obstacles to automated monitoring, including the automation of tree-species identification in diverse forests, and the assessment of forest structure in high-density forests. These obstacles are particularly relevant to tropical forests, which are typically dense and diverse. We also identify battery lifetime as a limitation to large-scale surveys, and one that is unlikely to be alleviated soon. Despite these caveats, available technology is adequate for automating small-scale assessments of some forest variables that are relevant to restoration, particularly in less dense, less diverse temperate and boreal forests. A fruitful approach may be to use intensive ground-level and low-altitude automated surveys, to calibrate data from satellite imagery that is subsequently applied to monitor restoration over larger areas.

Key words: automated forest restoration monitoring, lidar, spectral imaging, unmanned aerial vehicle, automated species identification, battery

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SETTING THE GOALS OF AUTOMATED RESTORATION MONITORING

Forest restoration is an essential component of global efforts to protect biodiversity and mitigate climate change. Here we review automated techniques for forest restoration. Any discussion of effective forest restoration first requires the definition of explicit goals. If forest restoration equates to restoration of ecosystem services, then the question can be rephrased in terms of ecosystem services: which ones do we want to restore? Ecosystem services are categorised into regulating, supporting, provisioning and cultural functions (MEA, 2005). Regulating services include greenhouse gas regulation, nutrient cycling and hydrology. Supporting services include habitat provision and soil formation. Provisioning services are the provision of food, timber and other resources for human consumption. Cultural services include the provision of wilderness value and existence value to humans. In deciding which ecosystem services will be the subjects of automated monitoring, we must take into account: i) which ecosystem services are valued by stakeholders, ii) which can be feasibly measured with automated technology and iii) which may be proxies for other, harder-to-measure ecosystem services.

To answer the first question, we must consider the preferences of different stakeholder groups. Recreational forest users are likely to prize cultural services, such as wilderness value and a few key charismatic components of biodiversity. Biologists, on the other hand, will put more emphasis on regulating and supporting services and on cultural services that relate to biodiversity, defined more generally. Resource and environmental economists may emphasise provisioning services and perhaps economically quantifiable regulating services (e.g., carbon sequestration can be quantified with carbon credits) or cultural services (e.g., provision of wilderness value can be quantified as eco-tourism revenue).

In answer to the second question, only a few of these ecosystem services are likely to be measurable with automated technology in the next decade or two. For those related to forest biomass and physical structure, including habitat availability and microclimate (SCHWARTZ et al., 2000; ANDERSON & GASTON, 2013, JUCKER et al., 2018, DEERE et al., 2020), remote-sensing technologies exist that can be deployed for both above-canopy surveys (ASNER, 2007; MASCARO et al., 2011; ASNER et al., 2012; JAAKKOLA et al., 2017; KELLNER et al., 2019) and, to a more limited extent, for below-canopy surveys (FORSMAN & HALME 2005; MCDANIEL et al., 2012; CHISHOLM et al., 2013). For ecosystem services, related to tree diversity (e.g., existence value), incipient technologies can provide coarse estimates from lidar and hyperspectral imagery (DINULS et al., 2012; FÉRET & ASNER 2012; SCHWEIGER et al., 2018). For ecosystem services, related to specific tree species (e.g., provision of sustainable timber supplies), distinctive plants can be identified from remotely sensed imagery (ANDERSON & GASTON, 2013). However, many ecosystem services, such as hydrology and soil formation, do not relate directly to any of these measurable indicators. This is especially true for some of the more abstract cultural services, such as wilderness value. However, advances in artificial intelligence may prove fruitful even here.

Fortunately, and in answer to the third question, many ecosystem services, though difficult to measure directly by automated means, are indirectly related to tree biomass and diversity. A forest is defined by the presence of trees taller than 5 m, with canopy cover of greater than 10% over an area of at least 0.5 ha (FAO, 2010). Consequently, focussing on forest biomass, as a primary indicator of restoration success, makes sense. Forests that have high values of standing biomass contain large carbon stocks (ZAKI & LATIF, 2017) and thereby contribute to global climate regulation; though young forests sequester new carbon faster than old-growth forests do (POORTER et al., 2016). High-biomass forests also provide humans with timber, non-timber forest products and recreational value. The biodiversity of other taxa, including insects and birds, is correlated with plant diversity and the presence of certain habitat structures, such as large trees (ZHANG ET AL., 2016, DEERE et al., 2020). This all suggests that tree biomass and diversity are good proxies for general biodiversity and associated ecosystem services. Thus, in this review, we focus on tree biomass and tree diversity, as key indicators of forest condition. They are relatively straightforward to measure and, directly or indirectly, indicative of many key ecosystem services.

The remainder of this chapter is structured as follows. In the section “Metrics of Forest Restoration”, we discuss how our two indicators — tree biomass and tree diversity — can be measured, both directly and indirectly. In the section “Technologies for Forest Restoration Monitoring”, we discuss technical aspects of technologies that can potentially automate these measurements. In the section “Above- vs Below-Canopy Monitoring”, we discuss above-canopy and below-canopy approaches to automated monitoring of forest restoration. Finally, in the section “Summary and Conclusions”, we propose a roadmap for future development of automated forest restoration monitoring.

METRICS OF FOREST RESTORATION

Measuring forest recovery is meaningful only insofar as appropriate targets for indicator variables can be set. It is crucial that restoration baselines and targets are set in context (ASHTON et al., 2001; LAMB et al., 2005). For example, targets ought to consider the initial biomass and diversity when restoration started, as well as local constraints on biomass accumulation and diversity for the site. If baseline data for the target site are not available, efforts should be made to find appropriate baseline sites that match the target site's abiotic conditions (HUETTNER et al., 2009; PÉREZ-CRUZADO 2014). Distance to intact forest should also inform expectations of forest recovery rates. With these guidelines in mind, we now discuss the metrics of tree biomass and diversity that are potentially viable for automated monitoring.

For estimating tree biomass, the most direct non-destructive method is first to calculate the volume of standing trees and then apply per-tree wood density values. Indirect methods involve measuring variables, such as top-of-canopy height, that are correlated with tree biomass (CLARK et al., 2011, SWINFIELD et al., 2019). Such indirect methods come with caveats: they must be calibrated, using field data and can be biased if calibrated using data from sites having different characteristics from the focal site (e.g., methods calibrated at dry sites will be unlikely to give accurate results at wet sites). Monitoring canopy height can also be used to detect ongoing disturbances, such as natural tree falls and illegal logging (MILLER et al., 2000).

For estimating tree diversity, direct metrics include species richness and Shannon diversity, but these may be impractical to measure, necessitating the use of surrogates. One approach is to measure the spectral diversity of the forest canopy. Spectral diversity is defined as the variation in reflectance spectra usually measured per unit area. Other options include summarising spectra to hypervolumes that describe multidimensional variation (SCHNEIDER et al., 2017), or by using an approach that counts the number of distinct spectral clusters (BONGALOV et al., 2019). Diversity is also assumed to increase with successional stage, especially in early stages (CHAZDON 2008a). However, measuring successional stage can be complicated, because multiple forest successional pathways are possible from the same initial condition (WALKER et al., 2007; CHAZDON, 2008b). The rate and pathway of recovery is governed by (1) the extent of degradation before restoration, (2) the degree of ongoing disturbance and (3) the influx rate of late-successional propagules (ASHTON et al., 2001; LAMB et al., 2005). Successional stage can be tracked using automated technology, by assessing the abundance of distinctive early-successional species, canopy cover and canopy height (D'AOUST et al., 2004; KALACSKA et al., 2007). Canopy cover may be a useful metric in the very early stages of restoration, but in tropical forests the canopy closes relatively quickly, when pioneers still dominate and the forest is far from its climax condition (KABAKOFF & CHAZDON, 1996; MONTGOMERY & CHAZDON, 2001). Thus, the abundance of certain species could serve as an indication that succession, towards a high-biomass, high-diversity state, is being retarded.

Tree physiology metrics may also be useful for monitoring the progress of forest restoration. These metrics include photosynthetic activity, nitrogen concentration, water stress and leaf area index (LAI). Context is again critical. High water stress, for example, may be a warning signal of restoration failure in a wet forest, but not in a seasonal forest. SALAMÍ et al. (2014) reviewed metrics, including normalized difference vegetation index (NDVI), greenness index, green normalized difference vegetation index and photochemical reflectance index. NDVI, in particular, is widely used to classify different land-cover types, for which it is broadly effective. However, it has similar limitations to canopy closure metrics, because NDVI saturates at fairly low values of LAI (WANG et al., 2005).

TECHNOLOGIES FOR FOREST RESTORATION MONITORING

We now turn to technologies that can be used to collect and analyse data for the purposes of estimating the metrics, discussed above. We focus on technologies for ground-level or low-altitude deployment, which can be feasibly implemented by practitioners at reasonable cost. Potential technologies for monitoring forest restoration can be divided into i) the platform and ii) the sensors mounted on the platform. An illustration of the kids of technologies we consider is shown in Fig. 12.2. These technologies, for forest monitoring, are also reviewed in GUIMARÃES et al. (2020), although without specific reference to restoration. We recognise that satellite imagery represents a valuable source of information for forest monitoring, but do not review this, because it is a large and well-developed topic in its own right, and in any case, satellite imagery must be calibrated with data from near-ground technologies (KELLNER et al., 2019).

Platforms

Potential platforms for forest restoration monitoring are (i) stationary platforms, (ii) mobile ground-based vehicles and (iii) unmanned aerial vehicles (UAVs). The most straightforward are stationary platforms. They can carry heavy payloads, but data are collected only from a single location. Ground-based vehicles overcome this limitation, but are restricted to relatively flat, solid paths, free of debris, often in heavily managed forests. The most feasible platforms, for automated assessment of forest quality over large scales, are UAVs.

For forest monitoring, two main kinds of UAV are suitable: (i) rotorcraft and (ii) fixed-wing aeroplanes (KOH & WICH, 2012; DANDOIS & ELLIS, 2013; LISEIN et al., 2013; ZARCO-TEJADA et al., 2014; GUIMARÃES et al., 2020). COLOMINA & MOLINA (2014) provide a useful overview of UAV systems, including sensors and software, for remote sensing. Both open-source and commercial software are available for guidance and ground monitoring (e.g., Mission Planner). This software is rapidly evolving and includes functions for navigation in three dimensions, automatic transect grids and the ability to trigger certain actions at specified times or locations.

Remote-piloted UAVs are widely available, but for truly automated monitoring, UAVs should be autonomous. Navigation software work well above the forest canopy, but software for autonomous, below-canopy surveys is still largely in development. Note that, at the time of writing, legislation governing UAVs is highly variable among countries and still in flux. The definition of UAV varies by country and usually applies above some weight threshold. Many countries require a permit to fly a UAV and UAVs are typically prohibited from flying above a certain height. Forest restoration practitioners should be aware of local legislation in order to understand the restrictions these impose on automated monitoring (see Chapter 14).

Sensors

Sensors, useful for forest restoration monitoring, include those that measure light from different parts of the electromagnetic spectrum, and those that measure sound. In the case of light sensors, wavelengths reflected or absorbed by the land surface, are detected as pixels of information. Sensors, useful for forest surveys, are lidar, visible-light cameras, multi- and hyper-spectral sensors. For forest monitoring with conventional cameras, off-the-shelf models (still and video digital cameras) are adequate for photogrammetry, including two- and three-dimensional spatial reconstructions (see p 176) (DANDOIS & ELLIS, 2010; ROSNELL & HONKAVAARA, 2012).

Lidar sensors are heavier than conventional cameras (1 kg or more) and more expensive, but they collect more precise structural information. While cameras record a passive signal of the incident light image falling on the sensor, lidar devices transmit a laser signal and record the time taken for light, reflected from surfaces, to return to the sensor. Since laser light penetrates thin or incompletely solid surfaces, such as canopy leaf layers, reflection may occur at multiple depths from the uppermost canopy to the ground surface. The ability of the sensor to record these multiple returns, allows lidar to reconstruct multilayer structures. This is driving its rapid adoption in forest monitoring (LIN et al., 2011; HEIKKI, 2013; TSUBOUCHI et al., 2014; CUSHMAN & KELLNER, 2019; JONES et al. 2020). At present, lidar is prohibitively expensive for many purposes, particularly compared with the low costs of basic UAVs. However, the demand for diverse lidar applications is driving the development of lighter and cheaper lidar devices, which will make their use for forest restoration monitoring more cost-effective (WALLACE et al., 2012).

Multi- and hyper-spectral sensors collect data over a broad range of wavelengths of the electromagnetic spectrum. While conventional cameras have sensors in three visible-light bands (red, green and blue), multispectral cameras have sensors that cover a greater diversity of wavelengths, from the infrared and visible regions. Hyperspectral sensors are able to measure reflected light across the electromagnetic spectrum, often from ultraviolet to short-wavelength infrared (400–2500 nm) within 200 or more consecutive bands (ADÃO et al., 2017). Because forest vegetation reflects light beyond the visible range, the additional information, provided by multi- and hyperspectral sensors, is of high value for vegetation monitoring, particularly for detecting plant species and measuring functional traits e.g. stress responses and leaf mass per unit area (ZARCO-TEJADA et al., 2013, ASNER et al., 2015, SCHNEIDER et al., 2017, SCHWEIGER et al., 2018).

Localisation technologies

Sensor information from forest surveys, is most useful if location data are available. Such data can be used to construct maps of the environment or to add information to existing maps. The ideal localisation techno-logy is GPS, but it is not available everywhere (e.g., steep valleys or below the canopy (see page 180)). Alternative technologies include ultrasound (FUKUJU et al., 2003; MEDINA et al., 2013) and ultra-wideband radios (GEZICI et al., 2005). These operate over short distances, and communicate their position using ground-based sensors of known position. Unfortunately, the set-up costs of such systems can be high. Another option is Simultaneous Localisation & Mapping (SLAM) (BACHRACH et al., 2011; DURRANT-WHYTE & BAILEY, 2006a; DURRANT-WHYTE & BAILEY, 2006b; RYDING et al., 2015; LI et al. 2016, ZAFFAR et al., 2018). With SLAM, inputs from platform-borne sensors, including lidar and visible-range cameras, are processed in real time, to create a map of the environment that is used for platform navigation. Advances in forest-based SLAM are anticipated, driven by demand for military and commercial applications. However, the geographical range of UAVs using SLAM is limited by the precision of the SLAM software, which decreases with distance, due to error accumulation. Despite their limitations, these alternative localisation technologies may serve as stepping-stones towards improved GPS, or may be used in conjunction with GPS.

Data processing: forest physical structure and tree biomass

Much of the data collected from autonomous vehicles that monitor forests can be processed offline. Data may be collected manually by operators, but preferably the vehicle would continually transmit data to a base station for intensive post-processing, and only store enough data on board to navigate within its environment (e.g., via SLAM). We now discuss offline processing tools, for assessing forest structure from visual imagery and lidar.

Photogrammetry and stereo-photogrammetry, from aerial photographs of forests, have long been applied to estimate stand size, canopy depths and stand volumes. The challenge for fully automated monitoring is to design algorithms that match or exceed the performance of humans in measuring these forest properties. For example, canopy openness can be automatically measured from aerial imagery, by applying thresholding algorithms that classify pixels as either canopy or gap, according to light intensity values, usually from a single light band. A basic version of the technique is straightforward to implement, but efforts should be made to exclude obliquely captured images and apply lens-specific, optical corrections, to ensure that measurements are standardised by area (JENNINGS, 1999). However, this approach has now been made largely redundant by more advanced photogrammetric approaches (see below).

Techniques for estimating forest physical structure from remotely sensed data rely on software that can create and analyse point clouds derived from visual imagery or lidar. In the case of lidar, techniques developed for manned aerial surveys (LISEIN et al., 2013) are mostly transferrable to UAV surveys (e.g. LIN et al. 2011; WALLACE et al., 2012; HEIKKI, 2013; ZAHAWI et al., 2015; SWINFIELD et al., 2019). In the case of visual imagery, point clouds are constructed by Structure-from-Motion (SfM) (WESTOBY et al., 2012; IGLHAUT et al. 2019), an advanced photogrammetry technique that reconstructs three-dimensional surfaces by identifying common features across multiple two-dimensional images (LISEIN et al., 2013; COLOMINA & MOLINA, 2014). Deployment of SfM in forests is possible from point clouds scanned either above (WESTOBY et al., 2012; ZAHAWI et al., 2015) or below the canopy (FITZGIBBON & ZISSERMAN, 1998; POLLEFEYS et al., 2004; ROSNELL & HONKAVAARA, 2012; PIERMATTEI et al., 2019). It does not require camera positions to be known, although this greatly aids the process and enables point clouds to be located in absolute space. Both proprietary (e.g., Agisoft Photoscan, EnsoMOSAIC, PIX4Dmapper) and open-source (e.g., EcoSynth, MICMAC, Visual SfM and Open Drone Map) software is available for implementing SfM (GUIMARÃES et al. 2020). The point clouds, derived from SfM, have the advantage that densities are orders of magnitude greater than those from airborne lidar, although terrestrial laser scanning and drone-mounted lidar also produce very high point densities. Analysis of dense point clouds is computationally intensive and therefore, high performance computer services, including clusters of graphical processing units and cloud-computing services, improve its feasibility (LAVY et al., 2015).

Point clouds from lidar or SfM can be processed to measure the height and structural properties of forest canopies as well as the size of individual trees (WULDER et al., 2012). An example of SfM is shown in Fig. 12.3. Canopy height is computed as the difference between the canopy and terrain surfaces. The surfaces are constructed using algorithms parameterised for site-specific topographic and forest conditions. Digital terrain models are estimated by applying statistical smoothing algorithms to classified ground points. Consequently, their accuracy is a function of the density of true ground returns and topographic variation. Point clouds from SfM can produce accurate digital terrain models, when canopies are open or discontinuous (ZAHAWI et al.; 2015, SWINFIELD et al., 2019). When canopies are closed, canopy height can be underestimated, but often to a predictable degree and can therefore be corrected. Point clouds from lidar can produce accurate digital terrain models, even for high-biomass forests on uneven terrain (PATENAUDE et al., 2004; WALLACE et al., 2012; ASNER & MASCARO, 2014; VAGLIO LAURIN et al., 2014). An example lidar point cloud is shown in Fig. 12.1. Comparison of point clouds from different time points can yield information about tree growth, as well as ongoing disturbances such as natural tree falls and illegal logging (MILLER et el., 2000).

Point cloud data can also be processed, to estimate individual tree parameters, such as height, stem diameter, crown diameter and volume (DALPONTE et al., 2011; WILLIAMS et al., 2019). Tree heights are detected as local maxima within the canopy height surface, by scaling the detection window according to tree size. Crowns can also be segmented, using algorithms that search for tree edges, based upon changes in height or spectral signals between adjacent points (HYYPPA et al., 2001; ERIKSON & OLOFSSON, 2005; HOLMGREN & LINDBERG, 2014; WALLACE et al., 2014; TOCHON et al., 2015). Several algorithms exist to implement crown segmentation; one example is shown in Fig. 12.1. The addition of spectral information can aid in segmentation but misalignment in space and contrasting spatial resolutions introduces an additional layer of complexity. Accurate measurement of particularly heterogeneous canopies may require forest-specific allometric relationships between crown diameter and tree height, to prevent unrealistically sized crowns from being delineated. Tree volume can be estimated using algorithms for individual stem segmentation (e.g., KELLNER et al. 2019).

Once data on individual tree parameters have been computed, they can be used to track tree growth rates or calculate stand-level parameters, such as stem-size distributions, biomass and carbon (PATENAUDE et al., 2004; ASNER & MASCARO, 2014; VAGLIO LAURIN et al., 2014). Estimates of the dimensions of the tallest or dominant sized trees can be used to infer site quality and thus the maximum potential biomass that can be attained at any given site, assuming that maximum stocking capacity is achievable where edaphic and climatic conditions are optimal. Estimating the properties of the sub-canopy is more difficult due to obscuration by the overlying canopy, but even here lidar is able to reconstruct vegetation density as the ratio of reflected to incident lidar energy. This technique is the basis of the Global Ecosystem Dynamics Investigation (GEDI) on board the International Space Station (DUBAYAH et al., 2014) and has been implemented successfully using discrete airborne lidar also (ARNQVIST et al., 2020).

Estimating forest biomass and structure, using the techniques described here, is most feasible in forests that have relatively low vegetation density or are deciduous, facilitating the scanning of comprehensive point clouds from above-canopy UAVs. Such forests include most temperate and boreal forests. For dense evergreen tropical forests, other approaches, including below-canopy UAVs, may ultimately be needed (see page 180).

Data processing: tree diversity

Monitoring tree diversity recovery at a restoration site, following implementation of management interventions, can be challenging. A robust tool for identifying tree species automatically would be the holy grail of tropical forest ecology and would enable spatial assessments of species distributions on unprecedented scales. In forest restoration projects, it would facilitate accurate estimates of both tree diversity and tree biomass — the latter via application of species-specific wood density values. However, at present, even the best statistical models, and indeed expert humans, can identify only a handful of tree species from remotely sensed imagery (MARTIN et al., 1998; PU, 2009; ERINS et al., 2011; GARZON-LOPEZ et al., 2013; BALDECK et al., 2015; WANG et al. 2019; NATESAN et al., 2020; SOTHE et al., 2019). These statistical approaches will continue to improve, and may become adequate for species-poor forests, but for species-rich tropical forests it is possible that we will never be able to distinguish the hundreds or thousands tree species that coexist in them from imagery alone.

One general approach to tree species identification is to classify pixels into species, based on their spectral properties. This can work for forests with relative few tree species, but the complexity of the classification problem increases rapidly with tree diversity. The essential problem is that the number of photo-reactive molecules and architectural arrangements, found in vegetative tissue, is limited and intraspecific phenotypic variation in spectral properties (driven by genotypic variation and environmental heterogeneity) is not necessarily low relative to interspecific variation. One option is identification based on spectral classification from conspicuous flowers, but this depends on surveys being frequent enough to capture potentially narrow flowering periods. Another approach is to classify species based on their geometry, derived from imagery points clouds. This includes the sizes of features such as leaves and branches, and repeating patterns, which can be measured using structural or textural metrics. Successful applications to date have involved only small numbers of species in temperate forests (e.g., KUMAR et al. 2012; OTHMANI et al. 2014; TORRESAN et al. 2017; SOTHE et al., 2020; KRŮČEK et al. 2020).

If species-level identification of trees proves infeasible in species-rich forests, an alternative would be to separate species into broad groups, such as functional groups. For example, disturbance-responsive species, such as pioneer trees, can have especially large leaves and open crowns, and concentrations of chemicals that support high rates of photosynthesis (NOGUEIRA et al., 2004). Another alternative is to measure the overall spectral or textural signature or diversity of a forest and to map this to estimate species diversity using pre-established relationships (DALPONTE et al., 2008; FRICKER et al., 2015). Such approaches may be sufficient during the early stages of succession, when diversity is relatively low, but perhaps not during the later stages of succession, when finer gradations of diversity become important for assessing restoration progress.

More sophisticated methods of tree species identification could improve biomass estimation at forest restoration sites as well, by allowing species-specific wood density estimates to be used in calculations. In the long term, it may be feasible to identify trees from DNA samples taken from the stem itself. At first, this would require UAVs to collect field samples and return them to the lab; later, *in situ* identification may be possible. The latter may sound implausible, but the cost of sequencing has fallen by over five orders of magnitude since the turn of the century and the size of sequencing equipment has shrunk concurrently. It will take substantial human resources upfront to create the DNA markers for thousands of forest species, but in some cases this work is already being done (KRESS et al., 2009; LAHAYE et al., 2008; STEELE & PIRES, 2011; KRESS 2017).

Batteries

Over the next few decades, the main factor, limiting development of autonomous forest monitoring, will be battery technology (GUIMARÃES et al. 2020), particularly below the canopy, where energy is constantly required to manoeuvre UAVs in three dimensions. In recent decades, progress in many technologies, relevant to automated forest monitoring, has been rapid e.g. micro-processor speed and DNA sequencing, but battery technology has lagged (SCHLACHTER, 2013). Whereas the transistor count on microprocessors has doubled roughly every two years, the doubling time of battery energy density has been 10 years or more. Indeed, battery technology is the current limiting factor in the development of many technologies, from vehicles to smart phones. The limitations of UAV batteries also prohibit the use of the most powerful sensors, because they are heavy and energy-demanding.

We predict that within a decade or two, most of the technical challenges of automated forest monitoring will be solved, but the range of vehicles and therefore the scope of monitoring efforts will still be limited by batteries. In the longer term, revolutionary battery technologies may emerge that will alleviate these limitations. In the meantime, innovative solutions may expand the potential scale of below-canopy surveys. For example, UAVs with the ability to float or perch would improve energy efficiency, while solar-powered charging stations could greatly extend operating times in the field. Alternative fuels, such as hydrogen fuel cells, have recently been developed for UAVs and should also be considered.

ABOVE- vs BELOW-CANOPY MONITORING

Above-canopy surveys are by far the most widespread and feasible strategy for forest restoration monitoring at present. They can be carried out with low risk of collision with trees or other objects, which means they can follow preset trajectories or waypoints and can be conducted by either fixed-wing UAVs or rotorcraft. Because fixed-wing UAVs have longer battery lives than rotorcraft, a single above-canopy flight can last from hours to almost indefinitely, as advances in solar powered flight have demonstrated (SACHS et al., 2009). Furthermore, can easily connect to Wi-Fi, telecommunications, and GPS networks. Many studies have reported successful flights of UAVs above the forest canopy or through cleared areas within forests (DANDOIS & ELLIS, 2010; LIN et al., 2011; WALLACE et al., 2012; ANDERSON & GASTON, 2013; ZAHAWI et al., 2015; JAAKKOLA et al. 2017; KELLNER et al. 2019), many using autonomous navigation.

Below-canopy monitoring is a useful complement to above-canopy monitoring. It can reveal a wealth of information about a forest's internal structure, including the distribution of stems and their biomass. Indeed, data from below-canopy surveys of some kind (whether automated or not) can be necessary to calibrate above-canopy methods for estimating forest biomass and structure. Below-canopy monitoring also opens up new possibilities for automated tree identification, based on bark or DNA samples. To date, most applications of automated below-canopy forest sensing have used stationary platforms (Watt & Donoghue, 2005; Forsman & Halme, 2005; McDaniel et al., 2012; Heikki, 2013; Tsubouchi et al., 2014). Other applications have involved humans carrying a sensor around inside forests (Ryding et al., 2015). Such methods do not constitute automated forest monitoring, but at least demonstrate the potential usefulness of mobile, below-canopy sensors. Several studies have used ground-based vehicles (usually remote-piloted, but sometimes autonomous), carrying sensors in forests (Miettinen et al., 2007; Rasmussen et al., 2013), but the application of these is likely to be limited to sparse, young forests or well-maintained plantations: most natural or semi-natural forests present too many obstacles (fallen logs, stumps, etc.) to ground-based vehicles.

The best long-term prospects for automated, large-scale, below-canopy, forest monitoring lie in rotorcraft, although flying rotorcraft autonomously through a forest understorey is fraught with technical difficulties. Navigation and collision detection are challenging tasks, compounded by unreliable GPS signals, due to interference or attenuation of the signal by the forest canopy. Rotorcraft and the advanced sensors required for navigation are energy intensive, which severely limits battery life. Nevertheless, some progress has already been made with relatively simple tasks, such as estimating tree diameters in a stand of planted trees (Chisholm et al., 2013).

SUMMARY AND CONCLUSIONS

We see a bright future for automated forest restoration monitoring, driven by exciting new and imminent technological developments in both software and hardware. However, for this technology to be effective, careful thought must first be given to fundamental practical considerations about how progress towards restoration is best assessed. We have proposed that restoration monitoring should focus on indicators that are relatively straightforward to measure and that reflect a broad array of ecosystem services. We have proposed tree biomass and tree diversity as two such broad indicators. Furthermore, we have emphasised the importance of defining baselines and of setting targets for restoration that are appropriate for the landscape context, i.e., that match, as closely as possible, the attributes of the original forest at the same location and that consider what is realistically attainable, given the current landscape matrix.

The technologies, on which automated forest restoration monitoring relies, fall into three broad categories: UAVs, sensors, and data-analysis software. Of these, UAVs, in particular, are an enabling technology for automated forest restoration: they permit cost-effective tracking of recovery processes over large spatial scales and at fine temporal resolutions. Surveys, based on UAVs, have further advantages in that they can be implemented rapidly in response to demand (e.g., a mast fruiting event) and data can be processed in near real time to direct management actions. Automated surveys are also likely to be more reliable than human-based ones. While they are not error-free, the errors that do occur are likely to be more consistent than errors in human-collected data and therefore easier to control.

Restoration practitioners can already draw inspiration from several recent studies that describe successful above-canopy forest surveys with autonomous fixed-wing drones. However, comprehensive restoration monitoring, at least in high-density tropical forests, requires not only above-canopy surveys but also below-canopy surveys, which are much more challenging (Fig. 12.2). To date, below-canopy surveys have been focussed on very specific tasks, such as high resolution, three dimensional, lidar scanning of small areas. Future advancements, including the use of SLAM to enable autonomous movement through vegetation, will expand the areas accessible to below-canopy UAVs.

Another major outstanding challenge for forest restoration monitoring is automated tree species identification. With potentially thousands of tropical tree species in a single square kilometre of forest (PLOTKIN et al., 2000), it seems unlikely that algorithms that rely on coarse structural or spectral characteristics, derived from image data, will ever consistently classify the majority of species. A better option, in the long term, may be for UAVs to collect genetic material for DNA barcode analysis — advances in genetic sequencing and barcoding are currently revolutionising species identification (KRESS et al., 2009; ZHANG et al., 2016; KRESS 2017).

Perhaps the biggest long-term limitation of above-canopy and especially below-canopy forest restoration monitoring is battery technology. This limitation is unlikely to be overcome soon, since, historically, the rate of improvement of battery efficiency has been slower than that of other technologies.

We emphasise that this review has been intentionally broad-ranging and has given only an overview of each relevant technology. We direct anyone, intending to carry out automated forest monitoring, to further reading in our reference list, in particular recent reviews on topics including UAVs (Torresan et al. 2017; Guimarães et al. 2020), SLAM (Li et al. 2016), SfM (Iglhaut et al. 2019), DNA barcoding (Kress 2017) and automated tree identification (Wang et al. 2019).

We foresee a near future, in which forest restoration monitoring relies on a combination of coarse, large-scale, above-canopy surveys and detailed, smaller-scale, below-canopy surveys (Fig. 12.2). The former will include analyses of satellite imagery, which is becoming increasingly available at high resolutions and large scales, heralding a "golden age" in remote sensing (Kellner et al., 2019). Initially, humans will continue to be heavily involved in some aspects of monitoring. However, the rising costs of manpower, falling costs of technology and its rising quality will all catalyse the move towards automation. In recent years, rapid development of both UAVs and sensors has been driven by military, engineering and commercial applications. These drivers should continue to deliver technological windfalls for forest restoration in the years to come.

Future priorities for research include: -

1. broader implementation of existing technologies, to assess which of them are already effective and identify those in need of improvements;
2. further development of tools for automated tree species detection and recognition;
3. reliable techniques for co-registration of geolocated data, to improve the precision of multi-temporal assessments;
4. a solution to below-canopy, autonomous, navigation problems;
5. creative workarounds to battery-life limitations, while we await the development of next-generation battery technology and
6. effective calibration of metrics from satellite imagery with data from ground-level and low-altitude surveys.

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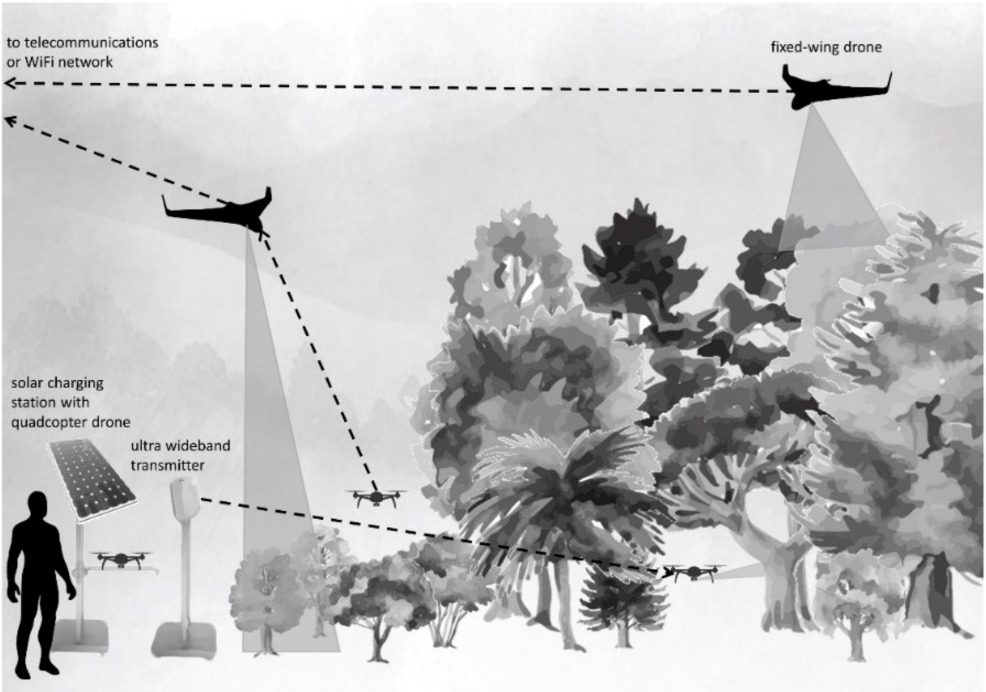

Figure 12.2 – Automated forest monitoring is likely to comprise a mixture of above- and below-canopy technologies, working together, to measure and track forests during the restoration process. This schematic demonstrates how one such integrated system may be designed, with fixed-wing unmanned aerial vehicles (UAVs) collecting data at the landscape scale, supplemented by more precise measurements from rotorcraft or ground-based UAVs, working at lower altitudes and below the canopy. Data are transmitted back to researchers either directly or indirectly via other drones and telecommunications networks.

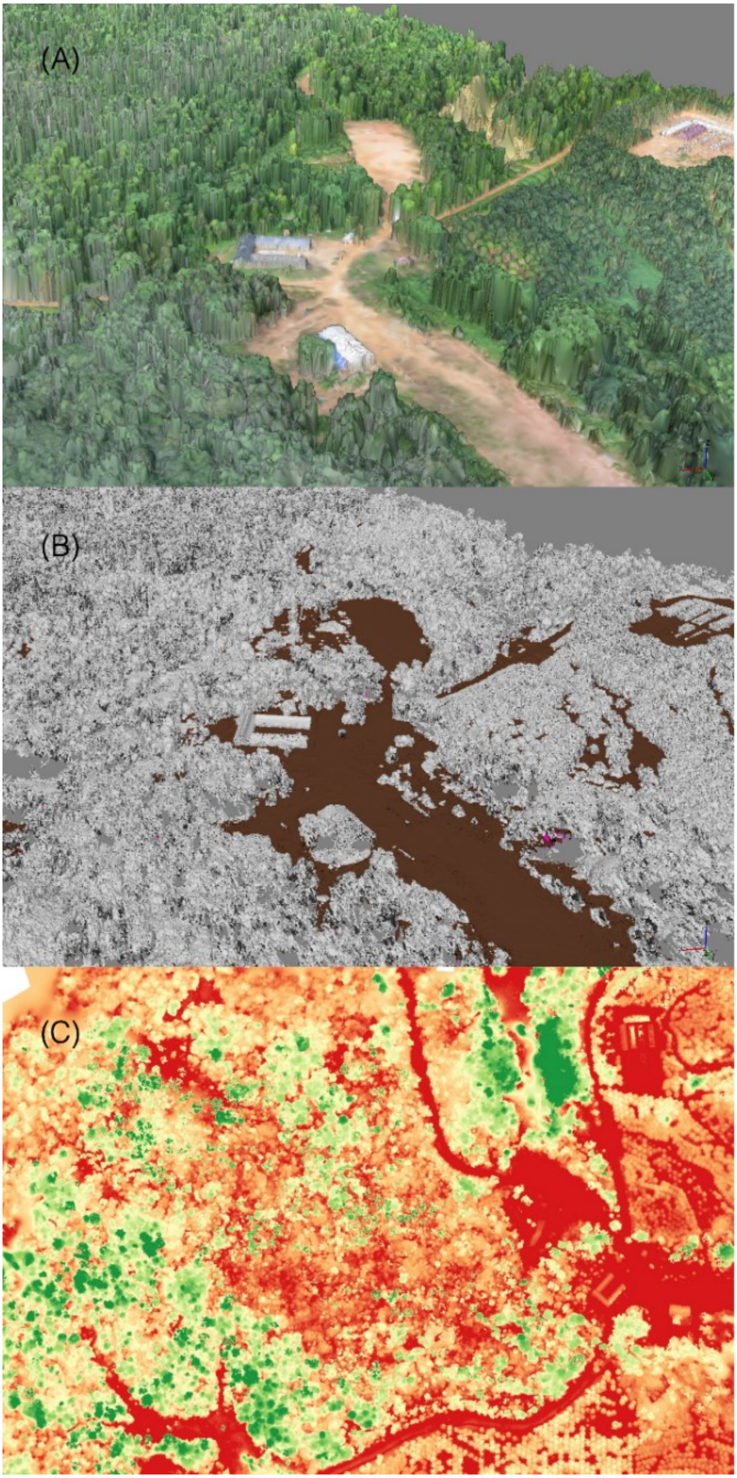

Figure 12.3 - A 3D model of regenerating secondary forest and oil palm at Hutan Harapan, Indonesia, produced using Structure from Motion (SfM):-

(A) The forest surface is shown in true-colour, reconstructed from UAV imagery.

(B) A false-colour image shows the result of automated ground classification (ground points are brown; non-ground points are white).

(C) The canopy height model produced via subtraction of the ground elevation from the model surface.