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Review paper

Integrating technologies for scalable ecology and conservation

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ABSTRACT

Integration of multiple technologies greatly increases the spatial and temporal scales over which ecological patterns and processes can be studied, and threats to protected ecosystems can be identified and mitigated. A range of technology options relevant to ecologists and conservation practitioners are described, including ways they can be linked to increase the dimensionality of data collection efforts. Remote sensing, ground-based, and data fusion technologies are broadly discussed in the context of ecological research and conservation efforts. Examples of technology integration across all of these domains are provided for large-scale protected area management and investigation of ecological dynamics. Most technologies are low-cost or open-source, and when deployed can reach economies of scale that reduce per-area costs dramatically. The large-scale, long-term data collection efforts presented here can generate new spatio-temporal understanding of threats faced by natural ecosystems and endangered species, leading to more effective conservation strategies.

Contents

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1. Introduction

Ecologists and conservation practitioners have proven themselves adept at incorporating emerging technologies into field data collection efforts (Pimm et al., 2015). The innovative use of technology is expanding the bounds of traditional ecological inference and conservation strategies (Snaddon et al., 2013). Continuing to expand efficient data collection in both time and space is crucial in the face of the enormous pressure that global changes are exerting on natural ecosystems (Rockström et al., 2009). Rapid habitat and biodiversity losses (Pimm et al., 2014), illegal wildlife harvest and trade (Milner-Gulland and Bennett, 2003), and climate change (IPCC, 2014) all affect ecosystems across the globe and increasingly require more than just field surveys to understand, monitor, and report on their effects.

Traditional field inventory plots and other sampling strategies are, and will continue to be, a crucial tool in the arsenal of ecologists for understanding local-scale processes and the functioning of ecosystems. Yet field surveys are costly to set up and maintain over many years (Berenguer et al., 2015), and they are extremely difficult to utilize in remote regions of the world. Just as concerning, in heterogeneous ecosystems field plots may actually provide biased estimates of ecological properties and processes (Marvin et al., 2014). The technologies we discuss here can help to overcome many of these shortcomings, especially when used in combination. Smart deployment and use of these technologies can open up new ecological scales to investigate the assembly, competition, dispersal, and migration of organisms and their interactions with the surrounding environment. Additionally, combating illegal activities such as poaching/hunting, logging, and encroachment require efficient monitoring and tangible evidence for investigating and prosecuting offenders. Preventing human–wildlife conflict, especially with large animals that can cause serious injury or death, often requires similar deployment of these technologies.

Here we provide descriptions and a synthesis of multiple technologies that can be deployed at different scales, with two hypothetical examples of how they can be integrated to increase the scale (both temporal and spatial) and dimensionality of ecological and conservation research. Increasing the resolution and area over which data are collected is important for identifying and mitigating threats to protected ecosystems, as well as understanding and uncovering ecological patterns and processes. Moreover, these data can be better integrated into dynamic global vegetation models (DGVMs) when the spatial and temporal scales accurately represent the process of interest (e.g., productivity, mortality). Most of the technologies discussed here or their associated data are low-cost, open-source, or freely available, and have proven applications for ecologists and conservation practitioners alike. The economies of scale achievable by these technologies can make any up-front expense for their purchase or development cost-effective. In Table 1, we provide example studies from each of the six main technologies that are described in more detail below. Our aim is simply to provoke discussion among researchers about the potential for integrating multiple technologies into their work, rather than providing a comprehensive critique of each emerging or established technology.

2. Remote sensing technology

2.1. Satellite

Satellite remote sensing platforms offer widespread geospatial coverage and, in many cases, long temporal records of Earth's biomes. However, most satellites (especially those satellite data providers offering free data access) lack the spatial resolution for organismic-level analysis, and often have limited spectral ranges, constraining their potential applications (Asner, 2015). While this is rapidly changing with the recent revolution in the way Earth-observing satellites are designed, built, and deployed (see discussion of cubesats below), the traditional large-platform satellites still have many advantages. An interactive overview of many operational satellites can be found at satsummit.github.io/landscape.

Government-sponsored satellite sensors have the longest temporal data archive of earth-observing images and are often freely available to the public. NASA's Landsat program just passed its 44th year of continuous operation, providing an incredible opportunity to analyze ecological and land use dynamics over very large areas (e.g., Hansen et al., 2013). There are many other optical multispectral and active sensors (e.g., radar, laser) that produce data at spatial resolutions ranging from 30 m to 1 km, offering data products for understanding vegetation dynamics and biomass, climate and weather patterns, and biophysical variables like surface temperature, soil moisture, and CO_2 flux (e.g., Goetz et al., 2009). Increased cooperation

Table 1
Summary of select studies by technology type.

Technology	Country/Region	Taxa/Ecosystem	Application	Reference
Satellite	Global	Forests	Forest cover change	Hansen et al. (2013)
Airborne	Peru	Forests	Whole-country carbon density	Asner et al. (2014)
UAS	Germany	Canopy trees	Assessment of flowering tree diversity	Getzin et al. (2012)
GPS telemetry	South Africa & Kenya	Elephants	Real-time monitoring of elephant movements	Wall et al. (2014)
Camera traps	Cambodia	Mammals	Habitat preference and activity patterns of 23 mammal species	Gray and Phan (2011)
WSN	New Mexico, USA	Shrubs	Microclimate variation in desert shrubs	Collins et al. (2006)

between the ecology and remote sensing communities could lead to improved biodiversity and ecosystem monitoring opportunities through publically-funded satellites and sensors (Skidmore et al., 2015).

Commercially operated sensors onboard traditional large satellite platforms typically offer much higher spatial resolution data (1–5 m), but at high cost. A typical archived (previously acquired) multispectral scene will cost at least \$20 km^{-1} with a minimum purchase of 25 km^2, making large or frequent acquisitions of images prohibitively expensive for many researchers. Commercial images are limited in their spectral resolution, often composed of four to eight band images, also known as multispectral images. Similar to government satellite sensors, these spectral ranges allow for visual analysis and the development of basic vegetation indices, but at (or near) organismal spatial resolutions.

The 'cubesat' (also known as small satellite or smallsat) revolution currently underway is providing new means to conduct earth observation and analysis. Cubesats weigh less than 10 kg (often only 1 kg), are about the size of a shoebox (Fig. 1), and are cheap (relative to large satellites) to design, build, and deploy. This allows for large constellations (orbitally-synchronized satellites) to be put into low-earth orbit, covering much larger areas of the globe simultaneously, but with less advanced sensors than those on large satellite platforms. One such company, Planet (San Francisco, CA, USA), is deploying a cubesat constellation with the goal of imaging the entire Earth once per day at <5 m resolution. Another smallsat company, Skybox Imaging (Mountain View, CA, USA), has HD video capability as well as multispectral imagery at 2 m resolution, but presently on a much smaller constellation. With the rapid advancement of smallsat technology and decreases in associated costs, the potential for more advanced sensors on larger satellite constellations will undoubtedly be realized over the coming years. Nearly real-time monitoring and analysis of research and conservation sites is not far off.

Fig. 1. Images of some of the described technologies. (Clockwise from top-left). One type of fixed-wing UAS during a hand-held launch (Image: Jeff Kerby). Another type of fixed-wing UAS being prepared for deployment (Image: Sander van Andel). A multirotor UAS being inspected before deployment (Image: Jeff Kerby). A Planet cubesat with body measuring 10 cm × 10 cm × 10 cm (Image: Planet). A tiger with GPS collar in India (Image: Ramesh Krishnamurthy). One node of a wireless sensor network used to detect illegal logging (Image: Rainforest Connection).

Accessing government and free commercial data has become much easier with new, web-based platforms that host these data. Almost all NASA-sponsored satellite data can be accessed through earthexplorer.usgs.gov at no charge. A more advanced image archive and search platform is Google Earth Engine (GEE), capable of rapid and sophisticated analysis of satellite imagery using the Google's cloud computing systems at no cost. Many necessary preprocessing steps (e.g., atmospheric correction, orthorectification) have already been applied to the imagery catalogue, and there are even derived composite products (e.g., NDVI) available. While utilization of satellite imagery traditionally required specialized technicians to process and interpret, the continued maturation of these platforms allows almost anyone to incorporate satellite imagery into their projects on some level.

2.2. Airborne

Over the past several decades airborne platforms have begun to fill a critical gap between the measurements provided in field studies and those by satellite-based sensors. At one extreme, field plots provide highly detailed measurements of the physiology, taxonomy, growth, and mortality of individual organisms (Gentry, 1988), while at the other extreme Earth observing satellites provide wall-to-wall coverage of ecosystem type, structure, and land-cover change. (e.g., Friedl et al., 2002). Advancements in sensor technology, image processing and analysis, and mission planning now allow measurement of ecosystem properties in plot-level detail at landscape-to-regional scales previously only possible with satellites, and at steadily decreasing cost.

While airborne remote sensing has long been used in forestry and agriculture (Colwell, 1964), a shift from basic analogue and digital photography to high-fidelity hyperspectral, active radar and laser, and passive thermal instrumentation has changed the field dramatically. The proliferation of these modern sensors mounted on aircraft operated by government, commercial, and non-profit entities has revealed ecological processes in great detail across spatial scales that have long eluded ecologists. Some of these data or resulting products are made available to the public (e.g., earthexplorer.usgs.gov, cao.carnegiescience.edu).

One such system, the Carnegie Airborne Observatory (CAO) Airborne Taxonomic Mapping System (AToMS, cao.carnegiescience.edu), is an airborne platform that fuses data collected simultaneously by three different sensors (Asner et al., 2012). Two optical hyperspectral imagers (also known as imaging spectrometers) and a waveform light detection and ranging (LiDAR) scanner are a powerful combination. Together they have been used to reveal forest canopy chemistry, biological diversity, carbon stocks, ecosystem structure, and even elephant and lion behavior (Dahlin et al., 2013; Féret and Asner, 2014; e.g., Loarie et al., 2013). Other airborne platforms are being developed for temperate ecosystem monitoring (neonscience.org) and snow mapping (aso.jpl.nasa.gov). The economies of scale achieved by airborne remote sensing are reducing the per-area cost tremendously. For example, in a recent project fusing CAO airborne data with satellite imagery, the cost (including aircraft, sensors, logistics, and data processing) to map forest aboveground carbon stocks throughout 132 million ha of Perú was less than $0.01 USD per ha (Asner et al., 2014).

2.3. Unmanned aircraft systems

The use of unmanned aircraft systems (UAS, also known as drones) is gradually gaining popularity and acceptance by the environmental community (e.g., Koh and Wich, 2012; Whitehead and Hugenholtz, 2014). The mainstreaming of this technology is partly driven by an increasingly challenging funding climate in the environmental sector: UAS present excellent cost-saving opportunities (compared with manual labor) in field-based applications such as the detection, monitoring and mapping of wildlife, their habitats and the wider landscape (Koh and Wich, 2012; Wich, 2015). These applications are relevant to species conservation, habitat protection and restoration, pest eradication, and watershed management. In addition, UAS can provide data at previously unavailable resolutions (e.g., ≤5 cm), allowing for increasingly fine-grained analyses of ecological questions (Anderson and Gaston, 2013).

Most UAS are fully autonomous aircrafts, with an on-board guidance system flying the UAS along pre-programmed waypoints over an area of interest (Fig. 1). They can be equipped with different camera systems for taking still RGB photographs, RGB video footage, thermal images, multi-band images, and even hyperspectral and LiDAR (Watts et al., 2012). UAS have monitored large mammals with UHF (Ultra High Frequency) or RFID (Radio Frequency Identification Technology) devices, substantially reducing costs compared to satellite and ground-based collaring and tracking operations (South African National Parks, unpublished data). UAS can be purchased off the shelf, or assembled from scratch as demonstrated by Koh and Wich (2012) for an array of conservation issues, allowing considerable flexibility in the choice of UAS. The latter approach is less-costly and allows malfunctioning or damaged parts to be replaced in the field, which is essential for remote areas. Some of the applications of conservation drones include mapping land use, surveying biodiversity, and monitoring illegal activities (for a review see Wich, 2015).

For example, the photographs captured by a UAS can be stitched together to produce a mosaic that provides detailed information on the type of land use, agriculture, and settlements in the landscape. (e.g., Whitehead et al., 2014). These images can also be processed to produce three-dimensional models of the landscape, such as terrain relief and forest canopy height (Dandois and Ellis, 2010) or they can be used to obtain data on species diversity and forest gap size (e.g., Getzin et al., 2012). Each photograph is automatically tagged with the UAS location coordinates when the picture was taken, allowing accurate

(1–2 m) geopositioning of the final imagery. The area mapped during one flight is a function of the ground resolution required and the flight duration of the UAS. Covering an area of ∼500 ha in a one hour flight is feasible with a ground resolution of ∼5 cm per pixel. Several small UAS can now fly for approximately an hour, with increasing flight durations allowing mapping of progressively larger areas, with several flights per day to expand the total area mapped.

The use of UAS could lead to significant savings in terms of time, manpower, and financial resources for conservation workers and researchers, but more assessments of the total costs of using UAS need to be made (e.g., Vermeulen et al., 2013). Such analyses should include the costs of personnel, computer hard and software, and UAS maintenance. These potential cost savings would increase the efficiency of monitoring and surveying forests and wildlife in the developing tropics. UAS are a potential game-changer and could become a standard item in the toolbox of field biologists everywhere.

3. Ground deployed technology

3.1. GPS telemetry

Animal movement and the ecological and evolutionary processes driving such behavior are fundamental characteristics of animal ecology and, when understood, enable insight into many biological phenomena. Animals move in attempts to find resources or to avoid risks, concurrently providing ecosystem services such as seed and nutrient dispersal (Côrtes and Uriarte, 2012) and acting as vectors for diseases and parasites (Altizer et al., 2011). Data on animal movement provides insight into the placement and maintenance of conservation corridors (Chetkiewicz et al., 2006) and movement itself facilitates connectivity between patches of fragmented landscapes (Mueller et al., 2014).

Technology to track animals and study their movement has undergone enormous advancement over the last several decades. Early reliance on VHF (very high-frequency) technology that required researchers to be in the field and in close proximity to tagged animals, possibly influencing their behavior, has being largely replaced with satellite telemetry using global positioning systems (GPS) that enable remote tracking and higher location accuracy (Cagnacci et al., 2010). Whereas before, telemetry data from wild animals were considered too sparse and inaccurate to enter the realms of cutting edge ecological research, smaller tags with longer battery life and vastly improved GPS technology (Fig. 1) have enabled large volumes of data to be collected from many more individuals and species (Kays et al., 2015). Recently, animal tags are being fitted with additional secondary sensors, allowing collection of physiological and environmental data. Accelerometers are being built into tags to measure fine-scale body movements, providing insight into energetics and behavior (e.g., Williams et al., 2014), while other electronic devices can be attached to record physiological measurements such as heart rate and internal temperature (e.g., Signer et al., 2010).

By making use of satellite or cell-phone communication networks, data from animal tags can be downloaded remotely in real time using mobile devices, circumnavigating difficulties around tag and data retrieval (and loss) and facilitating immediate responses to changes in animal locations (Kays et al., 2015). This provides much needed assistance to conservation managers who can receive alerts when problem animals leave predefined areas or acquire real time locations on endangered species that frequently come into contact with people (Wall et al., 2014). As the quality and type of tracking data have improved, so has the ability to measure the environment through which animals move. Remote sensing techniques provide extensive and continually improving measurements of ecosystems, and when combined with high resolution telemetry data can be a powerful tool to understand animal movement and habitat preference (Davies and Asner, 2014).

Further improvements to animal tracking technology can still be made, and some caution is required in the use of the technology (Hebblewhite and Haydon, 2010). Tag size is still too large for placement on many small birds and mammals (Kays et al., 2015), and although some studies have tracked insects (e.g., Ovaskainen et al., 2008), they are largely excluded from animal movement studies. There are also challenges around location accuracy, especially when attempting to match telemetry data with high resolution remote sensing. Ethical considerations and potential behavioral adjustments induced by tagging also need continual attention with concerted efforts to reduce adverse effects. However, the knowledge that has been gained through animal telemetry and the prospects for future discovery are enormous. Kays et al. (2015) suggest that we are moving into a 'golden age' of animal tracking science and are beginning to use animals to inform us about crucial changes to the planet and to make predictions of future change, moving from simply studying animals, to using animals to study the planet.

3.2. Camera-trapping

One of the most pressing problems faced by animal ecologists is choosing the most appropriate method for surveying and monitoring populations (Breck, 2006). Traditional methods such as live-trapping may increase the risk of injury to an animal and cause behavioral avoidance (or attraction) to the traps. Direct observations at points and along transect lines may also affect behavior due to the physical presence of the researcher, and are often difficult due to dense vegetation or clumped distributions of the target species. Terrain, remoteness, or weather conditions may preclude repeat visits by survey teams, making it difficult to replace baits or conduct replicate counts.

Camera-traps solve many of these issues by collecting animal movements in space and time through time-stamped photographs. Camera-traps do not require the researcher to be present and can be hidden or camouflaged to produce relatively unbiased samples. They can be established in any terrain or habitat and operate for as long as the power source allows. Camera-trapping can be more efficient than other survey methods, especially for rapid assessment of biodiversity (Silveira et al., 2003).

Modern digital camera-traps are remotely triggered by infrared sensors and are much less obtrusive, although sound and light produced by cameras vary by make and model (Meek et al., 2014). Camera traps can be set to take multiple photographs at desired time intervals, thus allowing multiple records of individual animals, and detection of family groups moving together. They can rapidly record and store hundreds to thousands of digital images on a single SD card, thus facilitating rapid sharing of data.

There is now a wide range of commercial camera-traps available to researchers, varying in detection angle and distance, field of view, trigger speed, recovery time, resolution, and price (Trolliet et al., 2014). There are a number of considerations when choosing a particular camera-trap device (see Glen et al., 2013; Kelly and Holub, 2008; Rovero and Zimmermann, 2013 for more detail). For example, if the study objective is to generate a rapid inventory of species presence, a low-cost ($40–100) model that takes photographs sufficient to identify species should suffice, although a non-intrusive infrared flash camera is preferable. However, if the objective is to enumerate populations of marked individuals, a much more sophisticated device with a high-resolution infrared camera is required.

The ecological applications of camera-trap data are diverse. Photos from single camera-traps can produce information on sex, age, breeding status and identity of individual animals, as well as other demographic parameters, and determine their activity patterns (e.g., Lynam et al., 2013). Photos from arrays of camera-traps can be used to measure movement and home range, and where individuals have identifiable coat patterns, camera-traps can be used to estimate population size (e.g., Burton et al., 2015). Using species detection/non-detection records and an occupancy modeling approach, it may be possible to predict the occurrence of rare species in a conservation area (MacKenzie et al., 2005). Camera-traps can help identify habitat preferences (e.g., Gray and Phan, 2011), although camera trap placement can bias results for different species (Harmsen et al., 2009), for example, if animals respond to human scent left on a device. Camera-traps have also been used for the study of ecological processes such as nest predation and plant–animal interactions (e.g., Pender et al., 2013).

Conventional camera-traps have been used to help improve detection rates of illegal human activity (Hossain et al., 2016). An adaptation of the camera-trap design can make it possible to transmit images or video in real time via SMS or MMS across local 3G telephone networks. Such wireless cellular camera-traps can detect individual animals such as problem elephants, or poachers, alerting park authorities who can then respond appropriately.

3.3. Wireless Sensor Networks

Wireless Sensor Networks (WSN) – composed of interconnected but spatially distributed autonomous monitoring devices – have great potential to aid in understanding ecological dynamics and protecting endangered species (Benson et al., 2010). Specially designed sensor networks can detect motion, sound, smell, and external environmental variables (e.g., temperature, humidity, light, etc.) in a non-invasive manner and in remote regions (Fig. 1). Distributed computing in WSN enables information to be collected remotely while processing only relevant data at a specific location, reducing data storage overhead or allowing increased sampling frequency. WSN have already been successfully used in military, industry, commercial, civil, and healthcare applications (Arampatzis et al., 2005).

Recent research on sensor networks has focused on networking techniques and networked information processing suitable for highly dynamic environments and resource-constrained sensor nodes. Sensor nodes have decreased in size and are much cheaper, resulting in the emergence of many new civilian applications from environment monitoring to vehicular and body sensor networks. Sensors are routinely deployed in very harsh conditions such as glaciers, on animals, or in very remote locations (e.g., Martinez et al., 2005). Low-cost, off-the-shelf sensor parts can be integrated with microcontrollers (e.g., Arduino) and microSD cards to create standalone sensor nodes that can communicate (via radio transmitters) with each other and/or a network hub. Soil moisture, tree growth, photosynthetically active radiation, water flow, and animal activity are just a few variables that can be continuously monitored remotely (Collins et al., 2006).

WSN technology is used not only to monitor remote locations but also to locate where events occur (Fig. 2). This is crucial for gathering evidence for illegal activity or uncovering subtle ecological interactions. WSN technology can be used for creating virtual fences, focal area monitoring, and/or behavior-specific surveillance. In a virtual fence set-up, a series of sensors are placed around the protected boundary of a target area and can identify an intrusion and its location, instantly communicating this to network monitors. A WSN exploits the capabilities of fiber optics, passive infrared, doppler radar, and other specialized sensor devices to create the virtual fence. Although the application of WSN in wildlife research and management is still in its infancy, they have become successful in the establishment of early warning systems and studying animal behavior. Alternatively, events such as gunfire (poaching), felling of trees, human or animal trespassing, and vehicle movement, among others, require monitoring of a focal area. This is best achieved with a WSN capable of sensing the target event, processing the signal to identify and locate the event, and communicating the event to a control station for initiation of a response if necessary. Finally, behavior specific surveillance is possible, for example by deploying sensor systems on natural trails for animal species that frequent trail networks for hunting and movement.

WSN technology functions best when integrating camouflage, low power-consuming devices, sophisticated signal processing software and hardware, and suitable packaging that can withstand hostile environmental conditions. WSN is a fast emerging field and ecologists and conservation practitioners alike can benefit significantly from new understanding

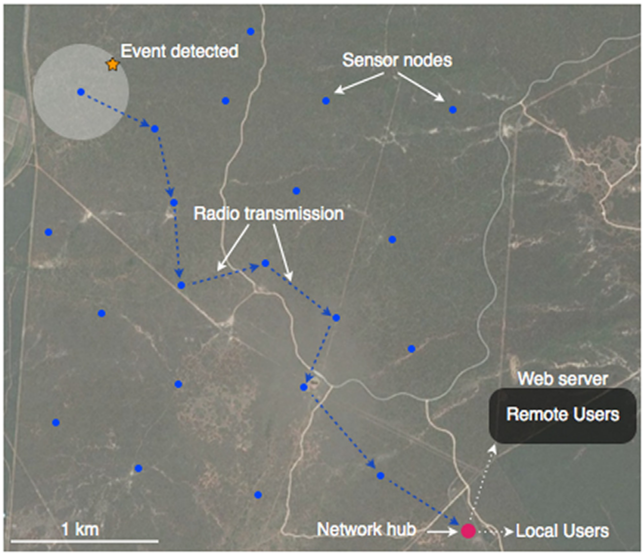

Fig. 2. Components and function of a hypothetical Wireless Sensor Network in Addo Elephant National Park, South Africa. An event is detected by a single sensor in the network, processed locally, and transmitted by radio among the network to a network hub. From there the event is sent to local users and a web server for remote users to monitor or analyze.
Source: Map data: Google, Digital Globe (2015).

of their target species or environments. Once deployed, this technology is a non-invasive method of wildlife research and conservation, without the need to physically capture animals, as required for radio collaring and tracking. WSN can provide important technological support for managing wildlife populations, including reduction in human–wildlife conflict, and uncovering the ecological dynamics of remote habitats. WSN tools have yet to be fully integrated in many real world applications for wildlife management and ecological research, partly due to lack of complete knowledge of such technology. However, there has recently been appreciable change in the exploration of WSN for conservation and research purposes, and a few experiments have already been taken up in India and Africa (pers. comm., R Krishnamurthy).

4. Data fusion and processing

4.1. Mobile devices and apps

The explosion of smartphones, tablets, and their innumerable associated software applications ("apps") has already revolutionized many industries and scientific fields around the world; the field of ecology is no exception. In their most basic form, these devices can be used to record data in the field more efficiently and without the added burden and mistakes associated with manual data re-entry—the device is simply synced with a computer or cloud network for further viewing and analysis. Whether using voice-to-text features or simply inputting numbers into a spreadsheet, smartphones and tablets undoubtedly give a field ecologist an advantage. Most current generations of phone and tablet devices have built in satellite navigation capability, but have only half the accuracy of standalone satellite navigation (e.g., GPS, GNSS) units (Olson et al., 2014), with further accuracy degradation in closed-canopy forests. However, using a standalone satellite navigation receiver allows work in remote areas and greatly increases positional accuracy under most conditions. These GPS (e.g., Bad Elf, Garmin GLO) and GNSS (e.g., EOS Arrow) receivers can link directly to the device through Bluetooth or a direct physical connection, providing precise navigation in the field. It may seem risky to expose an expensive piece of electronics to harsh outdoor conditions, but either a simple plastic bag or a more expensive water- and shock-proof case will adequately protect most devices. Some manufacturers even offer 'ruggedized' versions of their products specifically for outdoor use.

However, navigating to and within field sites is just part of the task. Data collection and organization are greatly enhanced by a number of apps, many of which are free to download and use on multiple device platforms. The free app iGIS allows caching of Google maps imagery for later use offline, uploads of custom base imagery (e.g., topographic maps, orthophotos, high-resolution satellite images, classification maps), creation of shapefiles (point, line, and polygon vector files), and linking photographs to geolocational data. While iGIS has a learning curve before the full functionality is unlocked, other options might be worth the price given their simplicity. GISpro may be expensive compared to most apps, but it unlocks a suite of easy-to-use features that turns a device into a mobile GIS unit. Undoubtedly, as these and other spatial data apps (e.g., WolfGIS, iGeoTrack) gain more usage among ecologists, field data collection will be transformed.

Myriad other apps are available to field ecologists that go beyond the collection of spatial data: real time weather and environmental conditions (e.g., Marine Weather Plus, RiverFlows), species identification (e.g., Plant-o-Matic, Map of Life), and, with a separate sensor, plant water content and molecular identification (SCiO). Numerous other apps are designed to enhance classroom learning, field education, and citizen science (e.g., iNaturalist, see Palumbo et al., 2012; Cybertracker, see Liebenberg et al., in press). A more comprehensive list of apps relevant to field ecology can be found at brunalab.org/apps, and custom apps can even be built to enhance the productivity of field ecologists (Teacher et al., 2013).

4.2. Computation

Data collection is only the first step; processing and analyzing many gigabytes of data from disparate sources requires new tools and techniques before ecological inference or conservation planning can begin. Increasingly, scientists are finding it difficult to avoid learning at least one programming language, and while the learning curve may be steep, the flexibility and efficiency benefits can be enormous (see software-carpentry.org for tutorials). As the scale of a project increases and the size of its associated data soars, knowing which software language and computational tools to rely on is important.

While the R language (cran.r-project.org) has become the *de facto* standard for data analysis and visualization among many ecologists, it is neither built for handling and processing very large datasets, nor does it have full geospatial functionality. While there are packages that can speed up processing ('renjin', 'Riposte'), improve memory management ('bigmemory'), and smartly handle geospatial data ('raster', 'rgdal'), there are alternatives that are worth the time to learn. The Python language (python.org) offers increased speed, better memory management, and can function as an integration tool for your entire workflow. Extremely rapid processing and analysis of geospatial data can be accomplished with GDAL (gdal.org) and SAGA (saga-gis.org) commands called from Python. Moreover, while many of the following computational resources can be used within R, they interface with Python far more readily.

Machine learning (ML) algorithms (e.g., random forests, support vector machine, neural networks) are a powerful approach for analyzing large datasets with many (hundreds to thousands) dimensions. Rather than assuming a data model as in traditional statistical modeling, supervised ML techniques use algorithms to uncover relationships in the data through a learning process (Breiman, 2001). The advantages of ML algorithms include less reliance on statistical assumptions, no need for data reduction, and greater predictive accuracies while still generating inferences about the data (Hastie et al., 2009). The open source platform H2O (h2o.ai) has a broad range of ML algorithms with highly efficient memory handling and the ability to easily scale-up analyses with parallel processing.

As the size and scale of a dataset increases, running analyses on a single computer processer becomes increasingly difficult. Most computers have multiple processors (CPUs) that are left idle when running an analysis. Parallel processing is a technique that dramatically cuts processing time by using all available CPUs on a computer, or hundreds to thousands of CPUs on a computing cluster. Whether utilizing a personal computer or purchasing time on a high performance computing cluster (e.g., Amazon Web Services), the packages 'foreach' for R and 'multiprocessing' or 'mpi4py' for Python are good starting points.

5. Integrated technologies for project scalability

5.1. Protected area management

Protected areas are critical for long-term conservation of endangered species but their effectiveness depends on how well they are managed (Watson et al., 2013). Many parks suffer from funding shortages and insufficient numbers of rangers and guards, leaving them unable to adequately manage encroachment, fire, hunting/poaching, and other unsustainable resource harvesting (Bruner, 2001). However, even parks with relatively large staff may not meet targets set for reducing threats and protecting populations of endangered species (Venter et al., 2014). More must be done than simply putting extra boots on the ground. Here, we provide an example of an open-source software tool for improving effectiveness of protected areas through an adaptive management approach.

The primary form of field-based monitoring in parks around the world is ranger/staff patrols. Ranger patrols have various mandates including research and monitoring, community engagement, and implementing law enforcement. In each role ranger teams collect data using combinations of notebooks, datasheets, mobile devices, GPS and digital cameras. Patrol-based monitoring works by setting up a flow of data from the field useful for park management and patrol planning (Stokes, 2010).

A new technology that facilitates this process is the Spatial Monitoring and Reporting Tool (SMART), open-source software developed through collaboration among conservation agencies and organizations concerned with improving site-based conservation area effectiveness (Fig. 3). Patrol teams can collect field data *via* an Android or Windows Mobile-enabled smartphone, tablet or PDA, and upload and manage the data through the SMART software. Users can create spatial queries and summaries about patrol movements, human activities, wildlife, or significant habitat features, and create custom reports. For example, how many foot patrols by a particular team resulted in encounters with people involved in illegal timber cases? Where did law enforcement teams record illegally killed elephant carcasses? A planning module allows target setting for patrols, teams, stations, or the entire conservation area, and monitor their progress towards achieving targets in real-time. Observations of animal carcasses or other evidence of illegal activity derived from local informants, researchers, tourists or the public can be added to the database and linked to patrol plans. As of August 2015, SMART has

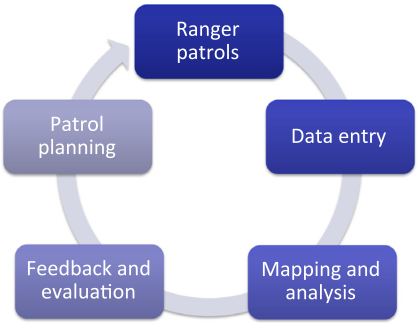

Fig. 3. The SMART approach for turning ranger-based data into information useful for park management and patrol planning. SMART creates flows of data in the form of point-based observations and tracklogs from ranger patrols. After initial processing (debriefing and data entry), mapping and analysis in the form of queries and data summaries, progress assessments, and reports can be produced. Reports are evaluated by the site manager and fed-back to ranger teams as patrol plans.

been implemented at 213 sites in 40 countries, with a number of national governments adopting SMART as a standard for law enforcement monitoring (smartconservationtools.org).

Remote sensing tools can supplement SMART data, particularly where forest loss or conversion is a primary threat. Landsat satellites acquire the same scene every 16 days, allowing images to be mosaicked to obtain cloud-free scenes. Each scene can then be directly compared with scenes from the same or earlier seasons. When areas of recent change are identified, the georeferenced image can be sent to law enforcement teams to enable field inspection and follow up actions. These approaches are useful for detecting deforestation on a range of scales from small (<10 ha) to very large (>10,000 ha), and for certain kinds of degradation. They are, however, not suitable for detecting low intensity forms of degradation such as firewood collection, highly selective logging, or the gradual effects of over-burning in deciduous forest. If the suspected areas are very remote, a fixed-wing UAS can be sent to capture high-resolution aerial photographs, helping authorities track down illegal loggers in national parks and provide evidence for their conviction. Furthermore, UAS equipped with a video camera can provide park rangers with real-time detection of wildlife poacher campfire many kilometers away. Using a UAS facilitates rapid responses to remote areas and a more comprehensive survey of the site than can be done from the ground.

Dry season fires are a common feature of the ecology of tropical dry forests, but are rare in denser evergreen and semi-evergreen forests. Therefore a cluster of fire locations in a dense forest area may indicate fire being used during forest clearance. FIRMS (Fire Information for Resource Management System) integrates remote sensing and GIS technologies to deliver global MODIS (MODerate Resolution Imaging Spectroradiometer) hotspot/active fire locations to natural resource managers and other stakeholders. MODIS Rapid Response makes the data available on the web within a few hours of satellite overpass (≥4 times per day), while GEE provides daily 1 km resolution FIRMS maps.

These data can be downloaded and queried so that fire locations are only shown within the areas previously mapped as dense forest, and far enough from the nearest area of open forest or non-forest to account for low data resolution. The data are then inspected to identify clusters of fires in the interior of dense forest, and mobile ranger teams are directed to make an inspection and appropriate interventions (Fig. 4).

WSN can provide significant support for surveillance and monitoring of protected areas. They can be used to create virtual fences to detect intrusions by humans, which can be covertly detected and reported to rangers who can decide on the appropriate response. WSN can also provide an early warning system for detecting the movement of animals and allowing managers to potentially avoid human–animal conflicts. This can build trust between protected area managers and local people, who are often at odds with various management practices. Road networks in protected areas can disrupt animal movement and lead to animal mortality from vehicle collisions. WSN can be used as an early warning system to traveling vehicles, avoiding or minimizing collisions. Finally, WSN can profile forest health and potentially be used for population estimation if combined with other technologies.

Combining patrol and remote sensing monitoring tools, along with intelligence derived from local informants is a model for protected area management that is replicable and scalable across conservation sites. The core of the system is to conduct regular field patrols with clearly defined strategic priorities, using local informant networks to help guide activities. Camera-traps used by monitoring teams, especially wireless models with capacity to instantly send recorded images of human intruders as MMS or email attachments, can identify threat hotspots in order to optimally position protection teams. Data on patrol activity should be analyzed using SMART to enable effective management oversight of staff performance, patrol targeting, and threat levels. Frequent inspection and comparison of Landsat images, while MODIS fire hotspot data, are also recommended.

5.2. Ecological dynamics

Collection of long-term data is critical to uncovering patterns and processes in ecology, but is usually limited in spatial scale, frequency, and/or duration. If integrated properly, the technologies discussed in this article provide a way to begin

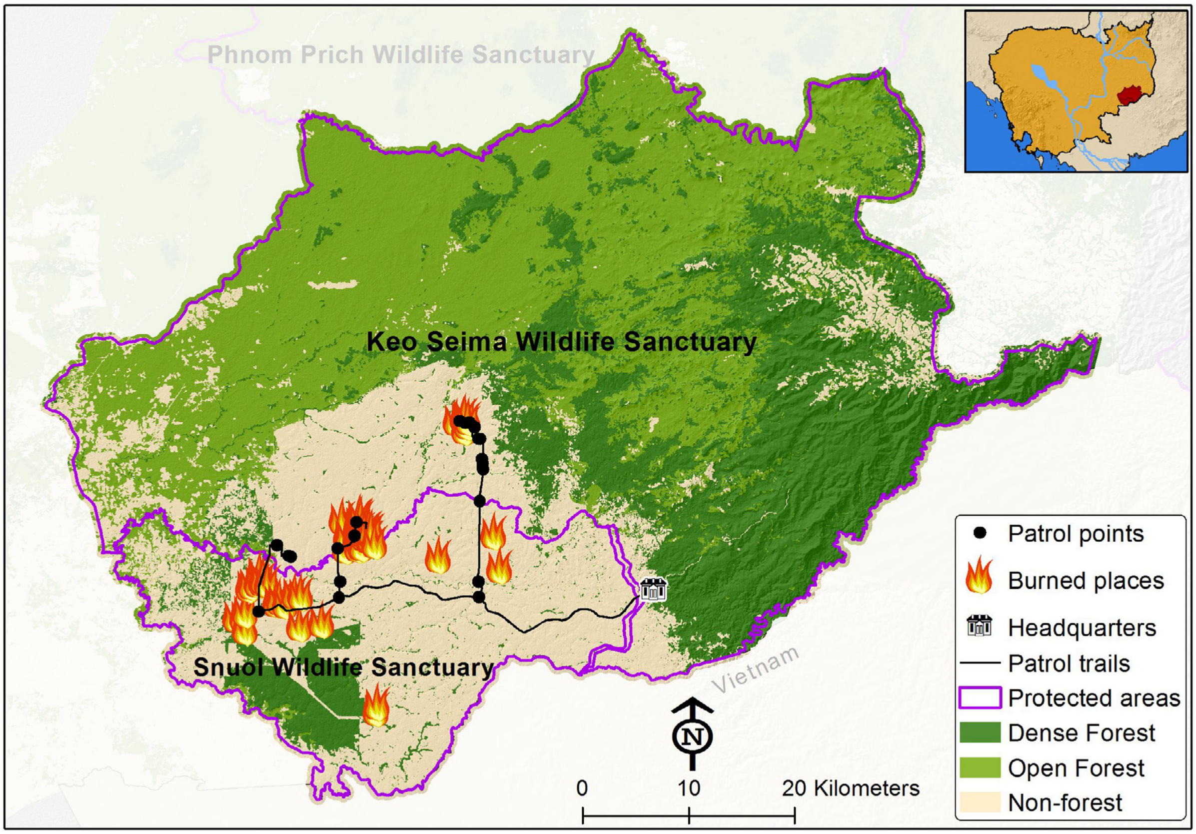

Fig. 4. Use of FIRMS (Fire Information for Resource Management System) to detect land clearance as evidenced from fire signals (orange stars) in the Snuol and Keo Seima Wildlife Sanctuaries, Cambodia. Ranger patrol routes and observation points for investigating encroachment are indicated in black. (Figure/Artwork: S. Phien, WCS Cambodia).

overcoming spatial and temporal limitations in ecological data collection. Here we provide a generalized example of integrating each piece of technology to collect data from a remote forested ecosystem.

For a regional context, the surrounding land cover can be assessed using GEE to pull together a cloud-free mosaic of recent MODIS imagery. The GEE platform has built-in algorithms for creating a land-cover map that can set the broader context and assess potential threats for the area of study. A function could be built to examine forest gap dynamics by utilizing the long-running Landsat time-series. The 30 m resolution Landsat data (available as far back as 1982) can pick up large treefall gaps and storm blowdowns. The deployment of an airborne imaging system such as the CAO or the ASO (Airborne Snow Observatory), allowing an enormous improvement in spatial and spectral resolution, would be ideal for producing a detailed baseline understanding of the area. Plant functional and chemical diversity can be mapped *via* airborne imaging spectroscopy, while airborne LiDAR can produce 3D vegetation structure and accurate digital elevation models (Fig. 5). A combination of targeted deployment of a UAS and regular analysis of cubesat imagery provide additional platforms for temporal investigation. A UAS can be programmed to fly close to the forest canopy for increased imagery resolution. Forest phenology, tree species identification, and certain types of wildlife surveys could be accomplished with these technologies at far greater spatial scales and temporal frequencies than ground-based surveys alone. In fact, researchers have been able to detect orangutans and their nests, elephants, rhinoceros, forest buffaloes, and even turtle nests in UAS-acquired images (e.g., Wich, 2015).

The high upfront expense of airborne imaging makes it challenging to implement, but becomes cost-effective at scales around 10^3–10^6 ha. Similarly, any decision to deploy or utilize a remote sensing platform is context specific, and depends on the required scale, frequency, location, and type of data. In each case, the relatively low cost of traditional field data collection should be calculated and weighed against the generally more expensive but higher data yields of remote sensing technology. Linking multiple platforms across different scales is an active area of research (Joshi et al., 2016) that needs further development before wide implementation by field ecologists and conservation practitioners.

With the exception of LiDAR, the sole use of remote sensing technologies will not provide great insight into the below-canopy dynamics of a forest. Instead, ground-based technologies can supplement remote sensing data across similar spatial and temporal scales through innovative deployments. Using a mobile device equipped with a GPS receiver, spatial features can be recorded in the field (e.g., hydrological and geomorphological boundaries) and features identified in remote sensing

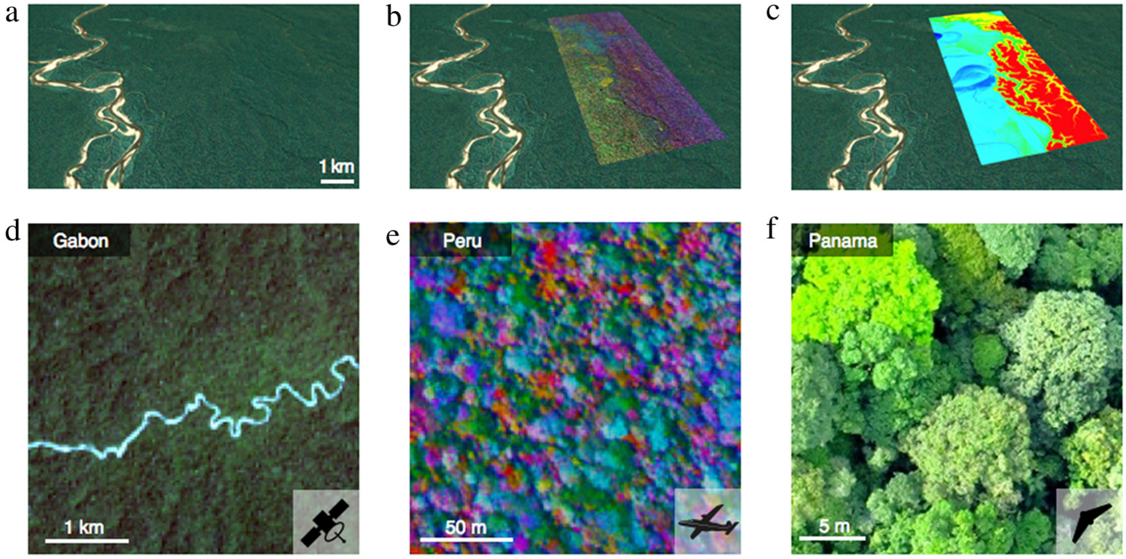

Fig. 5. Imagery from a variety of remote sensing platforms and sensors. (a) True color Landsat (source: Google Earth) image of a forested landscape in Madre de Dios, Peru. (b) Same as in (a) but with CAO imaging spectroscopy overlay. (c) Same as in (a) but with a CAO digital elevation model (elevation gain: blue to red) overlay. (d) Example true color image of Landsat 8 (30 m pixel resolution) from a forest in Gabon. (e) Example image of tree canopy chemical diversity derived from CAO imaging spectroscopy (2 m pixel resolution) from a forest in Peru. (f) Example true color image from a UAS (10 cm pixel resolution) from a forest in Panama. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

imagery can be verified (Barbosa et al., 2016; Marvin et al., 2016). Having multiple sources of preprocessed imagery available on a mobile device streamlines the collection of notes, the creation of vector (i.e., point, line, and polygon) data, and the capturing of geotagged photos on fundamental characteristics of a site.

Once the basic spatial layout and features of a site are cataloged, environmental data (e.g., rainfall, soil moisture, temperature, humidity, light) can be captured using cheap sensors, allowing for a large, low-cost network of environmental monitoring nodes. Even illegal logging can be detected in real time using re-purposed cellphones (Gross, 2014). The extremely low power requirements for such sensors may allow long-term, continuous operation *via* small solar panels—even in the forest understory. More advanced sensors such as those with camera, audio, or video capabilities might be more difficult to deploy in large numbers due to increased expense and power requirements. When used in combination with camera traps and/or GPS tags on animals, these larger sensors can conduct wildlife community/population surveys or acquire detailed data on species-specific behavior.

The deployment of sensors under a forest canopy, especially in closed canopy tropical forests, makes remote acquisition of data difficult. Developing these sensors as a WSN and using a UAS to periodically collect their data is a potential solution. In this setup, the WSN transmits data among the sensors to a central data collection hub placed either in a forest opening or in the forest canopy. A UAS could be dispatched to fly over each hub and acquire the data, and programmed to transmit instructions and code updates back to the WSN. Wider deployments of camera traps may be enabled by using a UAS to download the pictures remotely. This approach would drastically lessen the need for arduous trips to each sensor location for manual downloads, with the added advantage of less human disturbance in sensitive areas.

All of the above examples allow for long-term (months-to-years) data collection and observation of a single area of study. The lost-cost and distributed nature of a WSN combined with multi-resolution remote sensing data products allow for a large (10^2–10^5 ha) area of study to be monitored in sufficient detail to offer new insights into remote habitats.

6. Conclusion

We offer a look at a range of established and emerging technologies that can be used by ecologists and conservation practitioners to increase the spatial and temporal scales at which they work. The spatial links between the data at each scale allows researchers to increase the dimensionality of their datasets and perform spatially explicit analyses and predictions. Most of the technology is low-cost and can be readily used with some time investment into training and building. Collaborations with existing users and developers can speed up the process and lead to novel applications or even altogether new technologies.

Of course, all of these technologies come with their obvious trade-offs and challenges. Many advanced and high-resolution satellite sensors will be inaccessible or remain very expensive to access. Airborne remote sensing of any type is not an endeavor to be easily and quickly undertaken, and will likely require developing partnerships with existing operators. UAS are often limited in their applications by the payloads they can carry or the amount of time and/or distance they can fly. Lack of access to reliable power sources will reduce the utility of any device that needs to operate for very long periods while deployed in remote areas. The continued advance in the performance of underlying technologies will solve many of these problems, while other technologies may become less expensive as governments invest more in technology research, commercialization, and transfer. It is critical for those researchers and conservation practitioners new to these technologies to spend time familiarizing themselves with all potential drawbacks. Every research and conservation project is different, and it may be more cost-effective to invest in additional personnel training and retention than a new technology deployment.

Finally, we do not mean to suggest that traditional field-based data collection using transects or plots are no longer necessary or useful. Rare plant species identification, soil and foliar chemical profiling, and microbial and genetic sampling are all examples of crucial pieces of information needed to fully understand an ecosystem, but are not currently accessible without manual, on-the-ground collection by researchers. We encourage researchers to continue fully embracing and integrating the technologies discussed here as a compliment to traditional methods when designing their fieldwork. Deployment and refinement of these technologies will continue revolutionizing ecological and behavioral sciences, as well as conservation management of natural systems and endangered species.

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