

Futurecasting ecological research: the rise of technoecology

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Abstract. Increasingly complex research questions and global challenges (e.g., climate change and biodiversity loss) are driving rapid development, refinement, and uses of technology in ecology. This trend is spawning a distinct sub-discipline, here termed “technoecology.” We highlight recent ground-breaking and transformative technological advances for studying species and environments: bio-batteries, low-power and long-range telemetry, the Internet of things, swarm theory, 3D printing, mapping molecular movement, and low-power computers. These technologies have the potential to revolutionize ecology by providing “next-generation” ecological data, particularly when integrated with each other, and in doing so could be applied to address a diverse range of requirements (e.g., pest and wildlife management, informing environmental policy and decision making). Critical to technoecology’s rate of advancement and uptake by ecologists and environmental managers will be fostering increased interdisciplinary collaboration. Ideally, such partnerships will span the conception, implementation, and enhancement phases of ideas, bridging the university, public, and private sectors.

Key words: 3D printing; bioinformatics; ecology; environmental monitoring; information technology; interdisciplinary science; Internet of things; long-range telemetry; smart environments; unmanned autonomous vehicles; wildlife management.

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INTRODUCTION

Ecosystems are complex and dynamic, and the relationships among their many components are often difficult to measure (Bolliger et al. 2005, Ascough et al. 2008). Ecologists often rely on technology to quantify ecological phenomena (Keller et al. 2008). Technological advancements have often been the catalyst for enhanced

understanding of ecosystem function and dynamics (Fig. 1, Table 1), which in turn aids environmental management. For example, the inception of VHF telemetry to track animals in the 1960s allowed ecologists to remotely monitor the physiology, movement, resource selection, and demographics of wild animals for the first time (Tester et al. 1964). However, advancements in GPS and satellite communications technology have largely

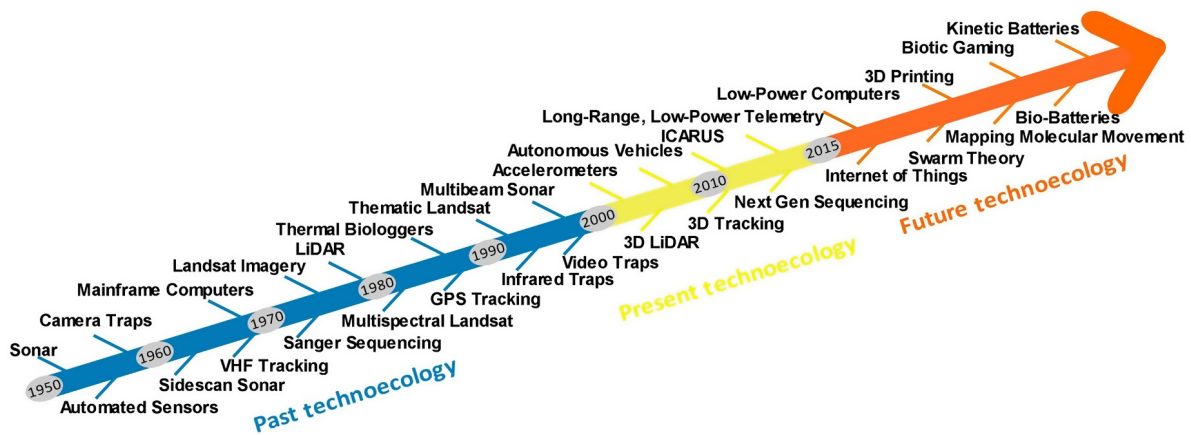


Fig. 1. Illustrative timeline of new technologies in ecology and environmental science (see Table 1 for technology descriptions).

supplanted most uses for VHF tracking. As opposed to VHF, GPS has the ability to log locations, as well as high recording frequency, greater accuracy and precision, and less researcher interference of the animals, leading to an enhanced, more detailed understanding of species habitat use and interactions (Rodgers et al. 1996). This has assisted in species management by not only highlighting important areas to protect (Pendoley et al. 2014), but also identifying key resources such as individual plants instead of general areas of vegetation.

Ecological advances to date are driven by technology primarily relating to enhanced data capture. Expanding technologies have focused on the collection of high spatial and temporal resolution information. For example, small, unmanned aircraft can currently map landscapes with sub-centimeter resolution (Anderson and Gaston 2013), while temperature, humidity, and light sensors can be densely deployed (hundreds per hectare) to record micro-climatic variations (Keller et al. 2008). Such advances in data acquisition technologies have delivered knowledge of the natural environment unthinkable just a decade ago. But what does the future hold?

Here, we argue that ecology could be on the precipice of a revolution in data acquisition. It will occur within three concepts: supersize (the expansion of current practice), step-change (the ability to use technology to address questions we previously could not), and radical change (exploring questions we could not previously

imagine). Technologies, both current and emerging, have the capacity to spawn this “next-generation” ecological data that, if harnessed effectively, will transform our understanding of the ecological world (Snaddon et al. 2013). What we term “technoecology” is the hardware side of “big data” (Howe et al. 2008), focused on the employment of cutting edge physical technology to acquire new volumes and forms of ecological data. Such data can help address complex and pressing global issues of ecological and conservation concern (Pimm et al. 2015). However, the pace of this revolution will be determined in part by how quickly ecologists embrace these technologies. The purpose of this article is to bring to the attention of ecologists some examples of current, emerging, and conceptual technologies that will be at the forefront of this revolution, in order to hasten the uptake of these more recent developments in technoecology.

TECHNOECOLOGY’S APPLICATION AND POTENTIAL

Bio-loggers: recording the movement of animals

Bio-logging technology is not new to ecology, incorporating sensors such as heart rate loggers, as well as VHF and GPS technology. Instead, bio-logging technology is being supersized, expanding the current practices with new technology. Accelerometers are being used to record fine-scale animal movement in real time, something which was only possible previously via direct

Table 1. Timeline of new technologies in ecology and environmental science, to accompany information in Fig. 1.

Technology	Description
Past	
Sonar	Sonar first used to locate and record schools of fish
Automated sensors	Automated sensors specifically used to measure and log environmental variables
Camera traps	Camera traps first implemented to record wildlife presence and behavior
Sidescan sonar	Sidescan sonar is used to efficiently create an image of large areas of the sea floor
Mainframe computers	Computers able to undertake ecological statistical analysis of large datasets
VHF tracking	Radio tracking, allowing ecologists to remotely monitor wild animals
Landsat imagery	The first space-based, land-remote sensing data
Sanger sequencing	The first method to sequence DNA based on the selective incorporation of chain-terminating dideoxynucleotides by DNA polymerase during in vitro DNA replication
LiDAR	Remote sensors that measure distance by illuminating a target with a laser and analyzing the refracted light
Multispectral Landsat	Satellite imagery with different wavelength bands along the spectrum, allowing for measurements through water and vegetation
Thermal bio-loggers	Surgically implanted devices to measure animal body temperature
GPS tracking	Satellite tracking of wildlife with higher recording frequency, greater accuracy and precision, and less researcher interference than VHF
Thematic Landsat	A whisk broom scanner operating across seven wavelengths and able to measure global warming and climate change
Infrared camera traps	Able to sense animal movement in the dark and take images without a visible flash
Multibeam sonar	Transmitting broad acoustic fan shaped pulses to establish a full water column profile
Video traps	Video instead of still imagery, able to determine animal behavior as well as identification
Present	
Accelerometers	Measures animal movement (acceleration) that is irrespective of satellite reception (geographic position)
3D LiDAR	Accurate measurement of 3D ecosystem structure
Autonomous vehicles	Unmanned sensor platforms to collect ecological data automatically and remotely, including in terrain that is difficult and/or dangerous to access for humans
3D tracking	The use of inertial measurements units devices in conjunction with GPS data to create real-time animal movement tracks
ICARUS	The International Cooperation for Animal Research Using Space (ICARUS) Initiative is to observe global migratory movements of small animals through a satellite system
Next gen sequencing	Millions of fragments of DNA from a single sample can be sequenced in unison
Long-range, low-power telemetry	Low-voltage, low-amperage transfer of data over several kilometers
Future	
Internet of things	A network of devices that can communicate with one another, transferring information and processing data
Low-power computers	Small computers with the ability to connect an array of sensors and, in some cases, run algorithms and statistical analyses
Swarm theory	The autonomous but coordinated use of multiple unmanned sensor platforms to complete ecological surveys or tasks without human intervention
3D printing	The construction of custom equipment and constructing animal analogues for behavioral studies
Mapping molecular movement	Cameras that can display images at a sub-cellular level without the need of electron microscopes
Biotic gaming	Human players control a paramecium similar to a video game, which could aid in the understanding of microorganism behavior
Bio-batteries	Electro-biochemical devices can run on compounds such as starch, allowing sensors and devices to be powered for extended periods in remote locations where more traditional energy sources such as solar power may be unreliable (e.g., rainforests)
Kinetic batteries	Batteries charged via movement that are able to power microcomputers

observation (Shamoun-Baranes et al. 2012). Using accelerometry, we can calculate an animal's rate of energy expenditure (Wilson et al. 2006), allowing ecologists to attribute a "cost" to different activities and in relation to environmental variation.

Bio-loggers are also causing a step-change in the questions we can explore in animal movement. Real-time three-dimensional animal movement tracks can now be recreated from data collected by inertial measurements units, which incorporate accelerometers, gyroscopes, magnetometers, and barometers. This technology has been used to examine the movements of cryptic animals such as birds (Aldoumani et al. 2016) and whales (Lopez et al. 2016) to determine both how they move and how they respond to external stimuli. The incorporation of GPS technology would allow for the animal movement to be placed spatially within 3D-rendered environments and allow for the examination of how individuals respond to each other, creating a radical change to the discipline of animal movement. Over the last 50 yr, we have gone from simply locating animals, to reconstructing behavioral states and estimating energy expenditure by using these technological advancements.

Bio-batteries: plugging-in to trees to run field equipment

Bio-batteries are new generation fuel cells that will supersize both the volume and the scale of data that can be collected. Bio-batteries convert chemical energy into electricity using low-cost biocatalyst enzymes. Also known as enzymatic fuel cells, electro-biochemical devices can run on compounds such as starch in plants, which is the most widely used energy-storage compound in nature (Zhu et al. 2014). While still in early development, bio-batteries have huge potential for research. Enzymatic fuel cells containing a 15% (wt/v) maltodextrin solution have an energy-storage density of 596 Ah/kg, which is one order of magnitude higher than that of lithium-ion batteries. Imagine future ecologists "plugging-in" to trees, receiving continuous electricity supply to run long-term sampling and monitoring equipment such as temperature probes and humidity sensors. Further, the capabilities of bio-batteries combined with low-power radio communication devices (see

Next-generation Ecology) could revolutionize field-based data acquisition.

Bio-batteries could greatly aid current technological projects such as large-scale environmental monitoring. For example, Cama et al. (2013) are undertaking permanent monitoring of the Napo River in the Amazon using data transfer over the Wi-Fi network already in place. The Wi-Fi towers are powered via solar panels, but within the dense rainforest canopy there is not enough light to use solar power to run electronics. If sensor arrays within the rainforest could be powered continuously via the trees, the project could run without a need for avoiding regions for lack of sunlight or using staff to regularly replace batteries.

Low-power, long-range telemetry: transmitting data from the field to the laboratory

Ecological data collection often occurs in locations difficult or hazardous to traverse, meaning that practical methods of data retrieval often influence sensor placement, limiting the data collected, but what if the data could be sent from remote sensors back to a central location for easy collection? Ecological projects such as monitoring the Amazon environment already do so using Wi-Fi towers (Cama et al. 2013), but Wi-Fi transmission range is limited (approximately 30 m). This can be extended with larger antennas and increasing transmission power, but in return consumes much more electricity. Other technologies are capable of transmitting data via either satellite (Lidgard et al. 2014) or the cell phone network (Sundell et al. 2006), but are likewise limited to locations with cell coverage or are prohibitively expensive. Low-power networks offer great promise for data transfer over large distances (kilometers), including the increasingly popular LoRa system (Talla et al. 2017). Long-range telemetry is already being used commercially for reading water meters, where water usage data are sent to hubs, transmitting data hourly, and a single battery could last over a decade (e.g., Taggle Systems; <http://www.taggle.com.au/>). Integrating such technology into ecological research would allow sensor deployment in remote areas where other communication methods are infeasible, for example, dense forests, high mountain ranges, swamps, and deep canyons. Such devices could also be

used to transmit information to a base station, resulting in faster data collection and more convenient data retrieval.

The Internet of things: creating “smart” environments

It is now possible to wirelessly connect devices to one another so they can share information automatically. This is known as the Internet of things (IoT), in which a variety of “things” or objects can interact and co-operate with their neighbors (Gershenfeld et al. 2004). Each device is still capable of acting independently, or it can communicate with others to gain additional information. Expanding on the use of low-power, long-range telemetry, IoT could be used to set up peer-to-peer networking to transfer data from one device to the next until reaching a location with Internet access or cell coverage, where more traditional means of transmission are possible. An attempt of such peer-to-peer transfer in ecology is ZebraNet: a system of GPS devices attached to animals (zebras) which transfer each individual’s GPS data between each other when in close proximity (Juang et al. 2002). Using this design, retrieving a device attached to one animal also provides the data from all other animals.

The applications of IoT go beyond the simple transfer of data. IoT technology effectively creates “smart environments,” in which hundreds of networked devices, such as temperature sensors, wildlife camera traps, and acoustic monitors, are connected wirelessly and are able to transmit data to central nodes. Using bio-batteries, such devices could run “indefinitely” (not literally, as components will eventually fail due to wear and tear in field conditions, which can be severe in some environments, e.g., very high/low temperatures, humidity, and/or salinity). From there, fully automated digital asset management systems can query and analyze data. Automated processes are increasingly pertinent with more long-term continuously recording sensor networks (e.g., National Ecological Observatory Network [NEON]). NEON is composed of multiple sensors measuring environmental parameters such as the concentration of CO₂ and Ozone, or soil moisture, all continuously-recording remotely with high temporal resolution, creating ever expanding environmental datasets (Keller et al. 2008). To make best use of such data

requires analysis at high temporal resolutions, which is not feasible to do manually by researchers, but possible with machine learning algorithms and other advanced statistical approaches.

Swarm theory for faster and safer data acquisition, and dynamic ecological survey

Swarm theory is a prime example of the complementary nature of technology and ecology. In essence, swarm theory refers to individuals self-organizing to work collectively to accomplish goals. Swarm theory relates to both natural and artificial life, and mathematicians have studied the organization of ant colonies (Dorigo et al. 1999) and flocking behavior of birds and insects (Li et al. 2013), in an attempt to understand this phenomenon. Swarm theory is already being used with unmanned autonomous vehicles for first response to disasters, investigating potentially dangerous situations, search and rescue, and for military purposes (<http://bit.ly/1Pel9Qz>). Exciting applications of swarm theory include faster data acquisition and communication over large geographic scales and dynamic ecological survey.

Swarm theory is directly applicable to the collection of remotely-sensed data by multiple unmanned vehicles, whether aerial, water surface, or underwater. Unmanned aerial vehicles (UAVs) are already being used for landscape mapping and wildlife identification (Anderson and Gaston 2013, Humle et al. 2014, Lucieer et al. 2014), and the data collected can be processed into high-resolution (<10 cm) to characterize the variability in terrain and vegetation density (Friedman et al. 2013, Lucieer et al. 2014). So far, however, such vehicles are used individually. By employing swarm theory, data collection could be completed faster by using several vehicles working simultaneously and collaboratively. Moreover, if vehicles were enabled to communicate with each other, data transfer would also be improved. Given the comparatively low costs of unmanned vehicles versus manned vehicles, such implementation would dramatically increase the efficiency of data collection while also eliminating safety issues. This efficiency could, in turn, allow for more repeated and systematic surveys, improving the statistical power and inference from time-series analyses.

Even more exciting than swarms simply being used to advance our capabilities in data

acquisition is the prospect of deploying them as more active tools for quantifying biotic interactions. The ability of a swarm to locate and then track individuals of different species in real time could revolutionize our understanding of key ecological phenomena such as dispersal, animal migration, competition, and predation. Swarms could be used to initially sweep large areas, and then, as individual drones detect the species/individuals of interest, they could then inform other drones, refining search areas based on this geographic information, and then detect and track the behavior of additional animals, in real time. An increased capacity to detect and measure species interactions, and assess marine and terrestrial landscape change, would enhance our understanding of fundamental ecological and geological processes, ultimately assisting to further ecological theory and improve biodiversity conservation (Williams et al. 2012).

This technology will however require careful consideration of the societal and legislative context, as is the case for UAVs (see Allan et al. 2015).

3D printing for unique and precise equipment

While 3D printing has existed since the 1980s, its use in ecology has primarily been as teaching aids. For example, journals such as *PeerJ* offer the ability to download blueprints of 3D images (<http://bit.ly/1MBPn1d>). However, 3D printing has many more applications. These include (1) building specialized equipment cheaply and relatively easily by using the design tools included with many 3D printers or by scanning and modifying products that already exist (Rangel et al. 2013); (2) building organic small molecules, mimicking the production of molecules in nature (Li et al. 2015); (3D printing at the molecular level even has the potential to create small organic molecules in the laboratory, Service 2015); and (3) printing realistic high-definition full-color designs in a number of different materials (<http://www.3d systems.com/>). Using such models, ecologists are able to print specialized platforms for sensor equipment (e.g., GPS collars) that fit better to animals. The use of 3D printing could go a step further, however, and create true-color, structurally complex analogues of either vegetation or other animals for behavioral studies. For example, Dyer et al. (2006) explored whether bee attraction was based on color or may also be associated with

flower temperature. Flowers of intricate and exact shape and color could be printed with heating elements embedded more easily and realistically than trying to build them by hand.

Mapping molecular movement for non-destructive analysis of nature

New developments in optical resolution and image processing have led to cameras that can display images at a sub-cellular level without the need of electron microscopes. Originally developed to scan silicon wafers for defects, this new technology is now being used to examine molecular transport and the exchange between muscle, cartilage, and bone in living tissue (<http://bit.ly/1DIYkD>). The development also highlights what can be achieved by cross-disciplinary and institutional collaboration, in this case optical and industrial measurement manufacturers Zeiss, Google, Cleveland Clinic, and Brown, Stanford, New South Wales universities. Together, they have also created a “zoom-able” model that can go from the centimeter level down to nanometer-sized molecules, creating terabytes of data.

These technology’s ecological and environmental applications are substantial, paramount of which is the non-destructive nature of the analysis, allowing for time-series analyses of molecular transfer. For instance, Clemens et al. (2002) examined the hyper-accumulation of toxic metals by specific plant species. Understanding how some plants can absorb toxic metals has promise for soil decontamination, but as stated by Clemens et al. (2002) “molecularly, the factors governing differential metal accumulation and storage are unknown.” The ability to not only observe the molecular transport of heavy metals in plant tissue, but also to change the observational scale, will greatly advance our knowledge of nutrient uptake and storage in plants.

Low-power computers for automated data analysis

Low-power microcomputers and microcontrollers exist in products such as Raspberry Pi, Arduino, and Beagleboard. In ecology, low-power computers have been used to build custom equipment such as underwater stereo-camera traps, automated weather stations, and GPS tracking collars (Williams et al. 2014, Greenville and Emery 2016). Notably though, following a surge in

hobbyists embracing the adaptability of low-cost, low-power, high-performance microcontrollers, large companies such as Intel have also joined the marketplace with microcontrollers like Edison (<http://intel.ly/1yekvNP>). Edison is low-power, but has a dual-core CPU, Wi-Fi, Bluetooth, data storage, inbuilt Real Time Clock, and the ability to connect a plethora of sensors from GPS receivers to infrared cameras (<http://bit.ly/1qHdor2>; Intel 2014). Cell phones and wearable devices are already integrating this technology. As an example, the Samsung Galaxy S8 cellular phone contains an eight-core processor computer with 4GB ram, cameras, GPS, accelerometers, heart rate monitor, fingerprint, proximity, and pressure sensors (<http://bit.ly/2ni8KRD>). Using microcontrollers such as these, it is possible to run high-level algorithms and statistical analysis on the device such as image recognition and machine learning. Not all microcontrollers are capable of running such complex data processes and other options will be required (e.g., microprocessors) instead, a situation that is likely to improve, however, with further development of the technology.

The ability to process data onboard has huge potential for technology's ecological application, such as remote camera traps and acoustic sensors. By running pattern recognition algorithms in the equipment itself, species identification from either images or calls could be achieved both automatically and immediately. This information could be processed, records tabulated, and a decision taken as to conserve, delete, flag the recorded data for later manual observation, or even transmit the data back to the laboratory. This removes the need for storing huge volumes of raw photographs or audio files, but instead just tabulated summary results. The equipment could be programmed to specifically keep photographs and acoustics of species of interest (e.g., rare or invasive species, or species that cannot be identified with high certainty) while deleting those that are not, and/or to save any data with a recognition confidence below a designated threshold for manual inspection. In terms of direct application to conservation, it is possible that this technology would allow intelligent poison bait stations to be built. Poison baiting is widely used to control pest species (Buckmaster et al. 2014), but the consumption of baits by non-target species can have unintended consequences

ranging from incapacitation to death, limiting the efficacy of the control program (Doherty and Ritchie 2017). Using real-time image recognition software built into custom designed bait dispensers, we could program poison bait release only when pest animals are present (e.g., grooming traps, <https://bit.ly/2IKAYAD>), reducing harm to non-target species.

TECHNOLOGICAL DEVELOPMENTS FLOWING INTO ECOLOGY

The technological developments from outside ecology that flow into the discipline offer great potential for theoretical advances and environmental applications. Two examples include personal satellites and neural interface research.

Personal satellites are an upcoming technology in the world of ecology. Like UAVs before them, miniature satellites promise transformative data gathering and transmission opportunities. Projects such as CubeSat were created by California Polytechnic State University, San Luis Obispo, and Stanford University's Space Systems Development Lab in 1999, and focused on affordable access to space. These satellites are designed to achieve low Earth orbit (LEO), approximately 125 to 500 km above the Earth. Measuring only 10 cm per side, the CubeSats can house sensors and communications arrays that enable operators to study the Earth from space, as well as space around the Earth. Open-source development kits are already available (<http://www.cubesatkit.com/>). However, NASA estimates it currently costs approximately US \$10,000 to launch ~0.5 kg of payload into LEO (NASA 2017), meaning it is still cost prohibitive, and the capabilities of such satellites are currently limited. Given the rapid expansion of commercial space missions and pace of evolving technology, however, private satellites to examine ecosystem function and dynamics may not be too far over the horizon.

Neural interface research aims at creating a link between the nervous system and the outside world, by stimulating or recording from neural tissue (Hatsopoulos and Donoghue 2009). Currently, this technology is focused in biomedical science, recording neural signals to decipher movement intentions, with the aim of assisting paralyzed people. Recent experiments have been able to surgically implant a thumbtack-sized array

of electrodes, able to record the electrical activity of neurons in the brain. Using wireless technology, scientists were able to link epidural electrical stimulation with leg motor cortex activity in real time to alleviate gait deficits after a spinal cord injury in Rhesus monkeys (*Macaca mulatta*; Capogrosso et al. 2016). Restoration of volitional movement may at first appear limited in its relevance to ecology, but the recording and analysis of neural activity is not. To restore volitional movement, mathematical algorithms are being used to interpret neural coding and brain behavior to determine the intent to move. This technology may make it possible in the future to record and understand how animals make decisions based on neural activity, and as affected by their surrounding environment. Using such information could greatly advance the field of movement ecology and related theory (e.g., species niches, dispersal, meta-populations, trophic interactions) and aid improved conservation planning for species (e.g., reserve design) based on how they perceive their environment and make decisions.

NEXT-GENERATION ECOLOGY

The technologies listed above clearly provide exciting opportunities in data capture for

ecologists. However, transformation of data acquisition in ecology will be most hastened by their use in combination, through the integration of multiple emerging technologies into next-generation ecological monitoring (Marvin et al. 2016). For instance, imagine research stations fitted with remote cameras and acoustic recorders equipped with low-power computers for image and call recognition and powered by trees via bio-batteries. These devices could use low-power, long-range telemetry both to communicate with each other in a network, potentially tracking animal movement from one location to the next, and to transmit data to a central location. Swarms of UAVs working together (swarm theory) could then be deployed to both map the landscape and collect the data from the central location wirelessly without landing. The UAVs could then land in a location with Wi-Fi and send all the data via the Internet into cloud-based storage, accessible from any Internet-equipped computer in the world (Fig. 2, Table 2). While a system with this much integration might still be theoretical, it is not outside the possibilities of the next 5–10 yrs.

Bioinformatics will play a large role in the use of “next-generation” ecological data that technocology produces. Datasets will be very large and complex, meaning that manual processing

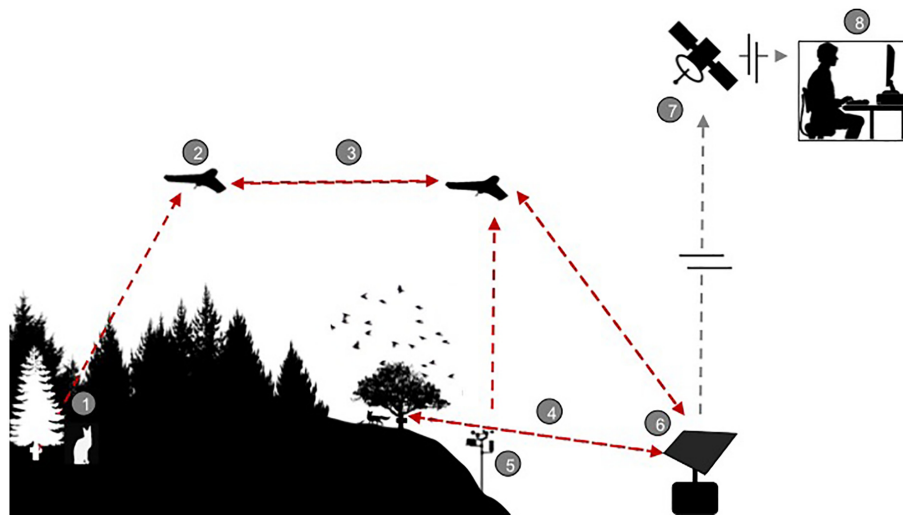


Fig. 2. Visualization of a future “smart” research environment, integrating multiple ecological technologies. The red lines indicate data transfer via the Internet of things (IoT), in which multiple technologies are communicating with one another. The gray lines indicate more traditional data transfer. Broken lines indicate data transferred over long distances. Once initiated, this environment would require minimal researcher input. (See Table 2 for descriptions of numbered technologies.).

Table 2. Description of elements of a future “smart” research environment, as illustrated in Fig. 2.

Number	Technology	Description
1	Bio-batteries	In locations where solar power is not an option (closed canopies), data-recording technology such as camera traps and acoustic sensors could run on bio-batteries, eliminating the need for conventional batteries
2	The Internet of things (IoT)	Autonomous unmanned vehicles could use IoT to wirelessly communicate and collect data from recording technologies (camera traps) located in dangerous or difficult-to-access locations
3	Swarm theory	Autonomous vehicles such as unmanned aerial vehicles could self-organize to efficiently collect and transfer data
4	Long-range low-power telemetry	Technology “talking” to each other, transferring information over several kilometers
5	Solar power	Environmental sensors, such as weather stations, could be powered via solar power and transfer data to autonomous vehicles for easy data retrieval
6	Low-power computer	A field server designed to wirelessly collect and analyze data from all the technology in the environment
7	Data transfer via satellite	There is potential to autonomously transfer data from central hubs in the environment back to researchers, without the need for visiting the research sites
8	Bioinformatics	With the ability to collect vast quantities of high-resolution spatial and temporal data via permanent and perpetual environmental data-recording technologies, the development of methods to manage and analyze the data collected will become much more pertinent

and traditional computing hardware and statistical approaches will be insufficient to process such information. For example, the data captured on a 1-km² UAV survey for high-resolution image mosaics and 3D construction is in the tens of gigabytes, so at a landscape scale datasets can be terabytes. Such datasets are known as “big data” (Howe et al. 2008), and bioinformatics will be required to develop methods for sorting, analyzing, categorizing, and storing these data, combining the fields of ecology, computer science, statistics, mathematics, and engineering.

Multi-disciplinary collaboration will also play a major role in developing future technologies in ecology (Joppa 2015). Ecological applications of cutting edge technology most often develop through multi-disciplinary collaboration between scientists from different fields or between the public and private sectors. For instance, the Princeton ZebraNet project is a collaboration between engineers and biologists (Juang et al. 2002), while the development of the molecular microscope involved the private sector companies Zeiss and Google. Industries may already have technology and knowledge to answer certain ecological questions, but might be unaware to such applications. Ecologists should also look to collaborate on convergent design; much of what we do as ecologists and environmental scientists has applications in agriculture, search and rescue, health, or sport science, and vice versa, so opportunities to share and reduce research and development costs exist.

Finally, ecologists should be given opportunities for technology-based training and placement programs early in their careers as a way to raise awareness of what *could* be done.

In the coming decades, a technology-based revolution in ecology, akin to what has already occurred in genetics (Elmer-DeWitt and Bjerklie 1994), seems likely. The pace of this revolution will be dictated, in part, by the speed at which ecologists embrace and integrate new technologies as they arise. It is worth remembering, “*We still do not know one thousandth of one percent of what nature has revealed to us*”—Albert Einstein.

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