Chapter 13. The future of technology in conservation

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Abstract
This final chapter discusses how conservation technology might evolve in the near future. The first section provides a global overview of the current scope of conservation technology. The second section focusses on the current limitations of conservation technology and describes advances that may help overcoming these constraints. I then discuss technological trends such as robotics and virtual reality, that are not widely used in conservation yet but offer promise to address current conservation challenges. I follow that with examples of integrating different technologies - with and without human intervention- in conservation research and management. Finally, I will touch on the barriers to integrating technology into conservation and propose solutions to overcome them.

Keywords: conservation technology; drones; IoT; robots; sensors; social networks, virtual and augmented reality

13.1 Current scope of conservation technology

Understanding and documenting biodiversity as well as the functioning of ecosystems constitutes an ambitious scientific challenge that needs urgent attention (Barnosky et al., 2011; Dirzo & Raven, 2003). Habitat loss and fragmentation, invasive species, pollution, over exploitation of resources and climate change are acting together to threaten species worldwide and the interactions among them (Arroyo et al., 2015).

As an interdisciplinary science - incorporating the physical, biological and social sciences as well as engineering - conservation relies on a variety of techniques, instruments and methods, including technological advances that facilitate data collection and analysis. Conservation technology specifically refers to devices, software platforms, computing resources, algorithms and biotechnology methods that support the conservation community (Greenville & Emery, 2016; Lahoz-Monfort et al., 2019; Pearce, 2012). This book dedicates a chapter to each of several key conservation technologies, describing hardware and software characteristics, function and application for research and management, as well as the social implications of using these devices. To facilitate a general overview of conservation technology, I summarize here current applications of these technologies, describe the temporal and spatial resolution they provide and review the implications for animal welfare and environmental impact (Table 1).

13.1.1 Research questions and conservation applications

Conservation science has a wide scope and addresses questions that range from individual behaviours to species distribution and ecosystem functions and their social context (see Sutherland et al. 2009 where "a hundred questions of importance to the conservation of global biological diversity" are suggested). Within this extensive conceptual framework, conservation technology can be categorized into data (1) collection and (2) analysis. Technology helps to determine the status and population trends of wildlife species, conduct habitat monitoring, identify ecosystem threats, and supports management decision-makers (Berger-Tal & Lahoz-Monfort, 2018). It also contributes directly to conservation action in the field, helping to detect illegal activities (e.g. poaching) and habitat restoration activities (Berger-Tal & Lahoz-Monfort, 2018).

The data collected with conservation technology are extremely variable. Aerial images acquired by drones and satellites serve to obtain spatial data about flora, fauna and their habitats, helping to estimating abundance and density and contributing to studies about wildlife distribution, animal behaviour and social organization (Chapters 2 and 3). The image and sound data captured by camera traps and acoustic sensors facilitate the detection and identification of animal species at specific locations, which serves to provide critical data for analyses into their distribution, density, behaviour and habitat selection patterns (Chapters 4 and 5). Animal-borne technologies such as GNSS and VHF units provide animal locations that serve to better understand animal movements and help conducting more efficient wildlife management programs (Chapter 6). Genetic information obtained with environmental DNA technology allows to detect and identify species presence, whilst molecular and physiological indicators are used in field-labs to help determine the health status of specific individuals and wildlife populations. These data are useful for conservation research, contribute to nutritional physiology, behavioural and life history studies and also for the management of human-wildlife conflicts, captive breeding programs and reintroductions (Chapters 7 and 8). Finally, data collection apps facilitate increased data collection for data to be processed faster, contributing to greater knowledge about biodiversity richness and to estimate population parameters (Chapter 9). Conservation technologies for data analysis have numerous applications. Geographic Information Systems (GIS, Chapter 2) software serves to process and visualize spatial information, which helps understanding ecosystem processes from local to global scales. Commercial software packages (e.g. Agisoft for photogrammetry with drone data), together with increasingly popular open source platforms (e.g. camtrapR (Niedballa, Sollmann, Courtiol, & Wilting, 2016)) facilitate more rapid and sophisticated data classification and analysis. The recent advances in artificial intelligence and machine learning are helping to reduce manual effort and costs otherwise dedicated to data analysis by automatically processing large volumes of data (e.g. automatic recognition of animals in camera trap images (Chapter 11, Tabak et al. 2019)). Finally, recent advances such as SMART (Chapter 10) allow integrating information from different field devices (e.g. mobile devices, GPS units) used by ranger patrols and to visualize data in a way that has improved management and enforcement, especially in rapid ranger responses to illegal activities (e.g. poaching).

13.1.2 Resolution

Broadly, conservation technology improves temporal and spatial resolution. Animal borne technologies such as light-level geolocators provide errors that can range between a few and hundreds of km (higher in latitude than in longitude), which is considered sufficient to study broad scale movements such as bird migrations (Fudickar, Wikelski, & Partecke, 2012; Lisovski et al., 2020). Argos satellites perform successive communications with animal transmitters and obtain locations ~ 150 m, generally considered acceptable for habitat selection, migration, and resource selection studies (Hebblewhite & Haydon, 2010). Similarly, triangulation using VHF transmitters can have up to 500m errors (Millspaugh et al., 2012). The locations recorded with data collection apps that are installed on smartphones use GNSS (Global Navigation Satellite Systems), such as the GPS (Global Position System), and provide an accuracy of ~ 5m and additional smartphone corrections can improve this to 1-2m (Garmin, 2020; National Coordination Office for Space-Based Positioning Navigation and Timing, 2020). Low-cost drone images can be georeferenced with an error of a few meters, which is generally sufficient to perform wildlife censuses and plant or animal counts in e.g. spatial ecology studies (e.g. Bushaw et al. 2019; Mulero-Pázmány et al. 2015). The use of additional RTK (Real Time Kinematic) systems, differential GPS, ground control points and postprocessing techniques can further reduce the spatial error of drone images to centimetres, allowing fine scale photogrammetry products such as point clouds, digital surface models and ortho-mosaics, where individual plants, animals and topographic features can be accurately detected and positioned (Casella et al., 2017; Casella, Drechsel, Winter, Benninghoff, & Rovere, 2020; Forlani et al., 2018).

The immediacy at which field data are obtained is an important parameter in conservation, especially in management, because numerous threats such as wildlife poaching, pollution or wildfires require rapid responses to be effective. In practice, immediacy depends on three steps: (1) data collection, (2) analysis, and (3) transmission to the end user. For data collection, remote devices (e.g. camera traps, acoustic sensors) or those that include a mobility component (e.g. drones) now offer on-board processing, and when networked via wireless communications [e.g. mobile phone networks, WiFi, Bluetooth (Augustin, Yi, Clausen, & Townsley, 2016)], can relay data to stakeholders in real-time. Wireless data transmission does require additional infrastructure, is typically more expensive than traditional systems and requires higher power consumption. The key advantage to on-board processing is the reduction in file size for transmission. Machine learning can now be implemented in edge computing to allow that, for example, only camera trap images that contain animals are transmitted to the end user and those with no relevant targets are discarded (Elias, Golubovic, Krintz, & Wolski, 2017).

13.1.3 Animal welfare and environmental impact

The impact of conservation technology on animal welfare varies with the technology in question. Animal-borne technologies require capturing and manipulating individual animals, and for animals to wear transmitters for a specified time. The tags can be embedded in collars (for mammals), attached as backpacks (for birds), or glued to different parts of the body (e.g. feathers, skin, turtle shells). Studies about transmitter effects have reported different results, from no significant effects to variable negative effects on the animals' behaviour, survival (injury, mortality), reproduction, and parental care as a result of the capturing, handling, sampling and tagging processes (Bodey et al., 2018; Dore et al., 2020; Omeyer, Fuller, Godley, Snape, & Broderick, 2019; Peniche et al., 2011; Puehringer-Sturmayr et al., 2020). To avoid undesirable effects on the marked individuals, safer tag materials are under development (e.g. Kay et al. 2019) and recommendations about the most appropriate transmitter weights and volumes for different purposes are periodically updated (Kenward, 2001; Silvy, Lopez, & Peterson, 2012).

Camera traps are static, small and discrete, so they are generally accepted as a non-intrusive method of studying animals (Long, MacKay, Zielinski, & Ray, 2008). Nevertheless, cameras produce sounds within most mammals' hearing range and some animals detect the noise or light that signals the camera is recording (Meek et al., 2014). Animals may respond to cameras with changes on their behaviour: staring at or fleeing from cameras or avoiding cameras altogether (Meek et al., 2014).

Drones have variable impact on wildlife depending on aircraft-type, size, engine type, and flight pattern - all that influence animal behaviour. Animal response also depends on the animal themselves, e.g. age and sex, time of year and the phenological context in which flights are conducted (Mulero-Pázmány et al., 2017). Animal reactions range from no response to the drone (or at least not visually noticeable), to physiological responses, fleeing behaviours or attacking the aircrafts (Ditmer et al., 2015; Mesquita, Rodríguez, Wich, & Mulero-Pazmany, 2020; Ramos, Maloney, Magnasco, & Reiss, 2018; Rebolo-Ifrán, Grilli, & Lambertucci, 2019). Following the ethical guidelines and recommendations for using these systems helps reduce drone impact on wildlife (Lyons et al., 2018; Mustafa et al., 2018; Rebolo-Ifrán, Graña Grilli, & Lambertucci, 2019; Vas, Lescröel, Duriez, Boguszewski, & Grémillet, 2015). These include reducing noise levels, maintaining the recommended distances for take-off and landing, manoeuvring smoothly and respecting minimum flight heights above the animals (Hodgson & Koh, 2016; Mesquita et al., 2020; Mulero-Pázmány et al., 2017; Vas et al., 2015).

Another type of environmental impact potentially derived from conservation technology is pollution, mainly caused by devices and material that for various reasons end up abandoned in the field, such as biohazard residues in field labs or eDNA, batteries and drone rests (e.g. Fuchs, 2008). Additionally, like with all field research, human presence is itself a disturbance, as people are required to install, check and maintain field-devices, collect samples and data, or use field labs. There is a lack of literature comparing the impacts on animal behaviour of conservation technology with traditional methods. Such systematic comparisons would provide a more complete picture of the costs and balances associated with new conservation tools.

13.2 Current limitations and expected improvements in conservation technology

Despite the recent explosion of conservation technology, there are limitations to any new device. We review them in this section along with the advances that may help overcoming them in the near future in the light of the latest developments (Table 2).

13.2.1 Power supply and data storage

Power supply is a general concern for conservation technology users. It constrains the autonomy of field deployed systems such as camera traps or acoustic sensors, limiting the amount of data that can be obtained and forcing revisits to remote installations, or recaptures of individuals marked with animal-borne technologies in order to change batteries. Drone users would like batteries that last longer and that are less expensive, because these restrict the number of flights that can be made on missions. In addition, stable electricity supply is necessary for long periods of time in order to recharge drone batteries (e.g. 1-2h / 6S 8A battery). The weight and volume of the batteries and multiple chargers frequently exceed that of the drone itself, which complicates transportation and logistics. Similarly, field lab and eDNA equipment need power supply for cooling reagents, samples, and analyses. As the general need for improvements in fast, low-cost and low-weight power supply is not exclusive to conservationists, but shared for other purposes by millions of other global users, the industry forecasts are for future batteries to last longer, be lighter, recharge faster and produce less pollution (Baran et al., 2019; Bitenc et al., 2020; Langridge & Edwards, 2020; Xiaomeng et. al. Liu, 2019).

In the meantime, solar panels constitute an alternative that has been integrated to provide power supply to camera traps (Voltaic, 2016), bioacoustics sensors (Rach et al., 2013), to power freezers, drone battery charging and other field devices. Solar GPS tags with rechargeable batteries are pervasive in studies that investigate bird movements because these are light, long-lasting, and capable of sending the data remotely (Silva, Afán, Gil, & Bustamante, 2017). However, because solar radiation is not constant, and in low availability can lead to battery drains, producing seasonal and circadian biases for solar GPS-tags is critical (Silva et al., 2017). Solar energy is also being exploited for drones to add power (which is translated into autonomy) without compromising the weight, size, or manoeuvrability of the aircrafts (Alta Devices, 2019). There are numerous examples of solar cells integrated on drone wings and fuselage, but their use in conservation studies is not generalized yet. Hydrogen fuel cells constitute a new option for powering drones, allowing them to operate longer than those equipped with batteries, and with lower thermal and noise signatures (Ballard Power, 2020)

Bio-batteries are a new generation fuel cells that convert chemical energy into electricity using low-cost biocatalyst enzymes and potentially obtaining the energy from organic components that are abundant in nature (Allan et al., 2018). This technology is still in its infancy, but it seems promising for conservation research, potentially allowing scientists to gather large volumes of data from remotely deployed devices.

The limitation of data storage is another constraint that forces conservationists to revisit remote installations when the internal hard drives or memory cards are full and no new data can be recorded in the field devices. Sensors are also evolving and produce higher spatial or temporal resolution files of increasing sizes (e.g. 8K drone images). According to manufacturers, memory cards with more capacity (e.g. up to 128TB maximum capacity) and faster registration protocols (e.g. 104-985MB/s) are expected to be widely available soon at affordable prices (Tung, 2018). The safe and fast storage and exchange of large volumes of data are also critical issues for camera trap users. As an example, 60 trap cameras with 32 GB SD can produce around 2TB in a standard three-month field deployment. Copying and emptying the memory cards to a computer to re-deploy them involves considerable dedication that - unless transmitted via wireless - needs to be done in the field. Storing these data volumes on external hard drives can cost around €200/year in external hard drives (without considering backup copies). In the era of big data, and despite the fact that there are accessible solutions for large companies, the standard academic user still experiences difficulties to transfer the material of a field campaign to a collaborator, since academic institutions do not usually have storage or transfer services for these large volumes, and free solutions (Dropbox Inc., One Drive or Google Drive) only allow for very limited storage space. It is expected that more efficient and safer platforms, such as state-of-the-art Enterprise File Sync and Share (EFSS) (Harrison, 2017) help address the problems of data storage and sharing at decreasing costs.

13.2.2 Image quality

The quality of the images and video captured with drones, camera traps or mobile phones determines the subsequent data processing options and the usefulness of the resulting data, especially if the objective is using automatic detection, classification and individual identification with machine learning algorithms. Low quality images may be enough to detect species presence, but higher resolution ones may be needed to identify individuals (for example, a specific fox according to its natural marks (Dorning & Harris, 2019)). Forecasts indicate that the quality of the lenses and sensors will improve along with the complementary systems that affect the final quality of the images (e.g. flashes, stabilizers, gimbals). In addition, the advances in the field of computational photography in the frame of edge computing allow analysts to treat the image on the device itself, for example combining several frames to obtain a better quality one (HDR) or dynamically focusing the object that moves between the different ones that appear framed (Chen, 2019). While the increase in image quality is desirable, the potential of it is sometimes wasted because the image processing software (photogrammetry, GIS software and machine learning) struggles to handle heavy files. Further, the increase in image quality or the treatments applied to the image may have consequences for analyzing them with machine learning. Consequently, drone and camera trap users often end up working with low quality versions of the images, splitting or down-sampling the raw data obtained in the field.

13.2.3 Connectivity

Connectivity allows data transmission from deployed devices to the end user. Data are generally transmitted via wireless connections and users access the data via internet or through mobile phone networks. Where data transmission costs are low, wireless communications can reduce the costs and efforts associated to field visits and accelerate data access for research or management purposes. The vast majority of the current data collection systems, such as camera traps or bioacoustic sensors, incorporate digitalization, which is the first step necessary for efficient data transmission. Once the data are digital, the transmission depends on the networks' availability. Mobile (e.g. 3-4G), Wi-Fi networks, satellite or radio are the most common ones. For example, 868MHz can be used for drone edge devices, and low-power wide-area network (LPWAN) such as LoRa (LoRa Alliance, 2020), that uses license-free sub-gigahertz radio frequency bands like 433 MHz, 868 MHz (Europe), 915 MHz (Australia and North America) and 923 MHz (Asia) is gaining popularity because it enables long-range transmissions (> 10 km) with low power consumption.

The field of wireless communications is rapidly improving in data transmission speed and spatial coverage. Several large companies have launched initiatives for global internet through satellite constellations (Crane, 2019; Oneweb, 2019; Sheetz, 2019) and stratospheric balloons such as Loon (X Development LLC, 2019), some of them with the promise of free service (chinadaily.com.cn, 2018). Others have suggested imaginative solutions such as using solar drones at high altitudes that would act as repeaters to provide greater spatial coverage (Tafintsev et al., 2019). In parallel, there are significant advances in the development of 5G (GSMA, Intelligence, GSMA, & Intelligence, 2014) that will support wireless networks with much higher speeds than the current 4G (Deans, 2020). 5G availability depends on a variety of factors including government regulation and technological improvements by mobile operators. Information on where 5G is available can be found online on different websites (e.g. (Asay, 2019).

There is an increase in the number of protected areas that have created local networks or repeaters that provide mobile or Wi-Fi coverage that can be used for conservation purposes. Several examples of these can be found in Europe [e.g. large-scale Singular Scientific-Technical Infrastructures such as Doñana National Park (RBD-CSIC, 2020), Africa (Serengeti, Ngorongoro Crater), and United States Parks (US National Park Services, 2020)]. Other initiatives, such as The Things Network (The things network, 2020) promote communities with low power devices to use long range gateways to connect to an open-source, decentralized network to exchange data with applications in several parts of the world including Asia, Australia and South America. Platforms such as LoRa (IRNAS, 2018; LoRa Alliance, 2020) also promote long-range connectivity in low power ways that are particularly interesting for research and management purposes. For example, Smart Parks in cooperation with African Parks, recently equipped an elephant with a LoRaWAN®/ GPS-sensor in Liwonde National Park (Malawi) that will send reliable and consistent locations every fifteen minutes for eight and a half years (more frequent that the current GPS collars that would allow one location/hour for five years). This technology makes a difference for the rangers because getting the animals' locations more frequently allows them to more rapidly react in their mission to protect elephants and avoid conflicts with surrounding communities (Smart Parks, 2020).

13.2.4 Sensor standardization and integration

Implementing technology over conventional methods typically allows for improved standardization, repeatability, and systematization of data collection (e.g. Hodgson et al., 2017). Data obtained by camera traps, drones or acoustic sensors can be reviewed afterwards, research design is repeatable across sites and seasons, and the sources of bias derived from the individual variability in terms of level of detection (auditory or visual) of human observers can be avoided (Anderson & Gaston, 2013). While technology offers improved standardization, data collection devices, even with similar manufacturer-listed specifications, still may have different sensitivities. For example, Heiniger and Gillespie (2018) showed that similar camera trap models varied substantially in their performance, providing different detection probability of small mammals in northern Australia. Because of this variation, it has been suggested that researchers include in their methods the specifications and configurations of the technological devices used and incorporate them in the analyses (Heiniger & Gillespie, 2018). Automatic data analysis tools such as image recognition by machine learning (e.g. camera traps for wildlife detection or vegetation classification in drone images) offer high levels of data processing standardization. These tools are convenient for systematic comparisons, but it is important to account for their variable detection and identification capabilities (see Chapter 11).

Specialized users of conservation technology require sensor integration, sometimes in the same device. For example, the use of camera traps with acoustic sensors is promising to monitor the ecological impact of human disturbance (Buxton, Lendrum, Crooks, & Wittemyer, 2018) and some research groups have begun to use these techniques together at large scales (Alberta Biodiversity Monitoring Institute, 2020, Colorado State University, 2020). The integration of camera traps with stereo cameras or LIDAR has been suggested to contribute to estimate animal characteristics, such as the individuals' size (Chapter 5). Because of the specificity of these sensor combinations, that may not be of interest of other industrial or consumers markets, it seems that the user community would need to push for their development via research and development projects or in collaboration with manufacturers.

13.2.5 Regulations

Legal barriers often limit scientific work that otherwise is technically feasible. For example, drones can be ready to fly, parked in solar charging stations, use take-off/landing pads located anywhere, and perform flights without any human intervention at different ranges. Potentially, these autonomous missions could be performed on natural areas that are scarcely populated minimizing the risks over humans. But drone legislation precludes fully autonomous operation in most of the countries, limiting the range of the flights (often to line of sight) and stating that operators should be always physically present and capable of taking control of the aircrafts in the field. This suggests there is a need to adapt legislation to the risks, addressing different drone uses (e.g. leisure, research) and areas (e.g. populated vs. unpopulated) and to seek consensus among countries (Cracknell, 2017).

13.2.6 Cost

Cost is an important limiting factor for the use of conservation technology. While being up-to-date using the last advances can be expensive, the access to technologies that have been on the market for some years is generally affordable and can complement or substitute traditional fieldwork (Koh & Wich, 2012; Welbourne, Claridge, Paull, & Ford, 2020; Welbourne, MacGregor, Paull, & Lindenmayer, 2015). The price of technological devices tends to decrease as technology evolves once development costs are amortised and production is standardized (Belton, 2015). However, there are some exceptions, such as mobile phones market, where prices - so far- have continued to rise for the new models (Priestley, 2020) and where outdated devices that can be less expensive produce functionality issues precluding customers to use them. While the final price of technological devices is influenced by production costs and, in principle, tends to decrease along time, other pricing strategies that consider the amount the customer is willing to pay, influence the price elasticity and are affected by competition and other factors.

There are some studies that compare the cost and efficacy of traditional methods with technological solutions, or different devices with each other. Welbourne et al. 2020 compares camera traps with traditional survey methods, concluding that camera-traps are a more cost-effective technique for surveying terrestrial squamates. Vermeulen et al. (2013) provide information of the cost of manned aircrafts versus drones for aerial surveys of elephants, indicating that while the drone cost is lower, the cost per area covered is almost ten times higher than that of a manned aircraft, but they exclude the costs of humans for analyses. Koh and Wich 2012 highlight the advantages of using inexpensive drones (USD2000) as a low-cost alternative to satellite and airborne sensors for surveying and mapping forests and biodiversity. Mulero-Pázmány et al. (2015) compare the use of GPS collars (33000€) with drones (5700€) to obtain cattle' locations and discuss the complexity of deciding which is the most cost-efficient method, because they provide complementary information. Mulero-Pázmány et al. (2014) discuss the costs and benefits of using drones for rhinoceros anti-poaching, including estimations on the personnel training costs and the lifespan of the specific drone used in that work, concluding that the cost of integrating drones in antipoaching tasks could be assumed by a medium size security company or institutions dedicated to anti-poaching surveillance. Jiménez López and Mulero-Pázmány (2019) review several studies that compare the cost of traditional methods with drones for conservation in protected areas in tasks such as water sampling, estimating birds nest densities and to perform forest inventories. While these comparative studies provide useful information on methodological considerations, technology evolves so fast that the costs, along with technical specifications, training, quality of the data obtained, and lifespan of the technological devices should be constantly reviewed and updated. Besides the commercial options, and as an alternative for those with short budgets, there is a growing community developing DIY (do it yourself) initiatives, the participatory model, and open source software platforms, such as those for camera traps (Nichols, 2020), drones (Anderson, 2020) bioacoustic sensors (Kim, Sanzeni, & Conaty, 2017) and Internet of Things (Postcapes, 2019).

13.2.7 Data management

Big data in ecology refers to large volumes of data not readily handled by the usual tools and practices (Hampton et al., 2013). Advances in sensors have resulted in the generation of troves of wildlife locations, images and sounds. Manually reviewing and analysing these data requires extensive resources. The advances in artificial intelligence, such as machine learning, may help discriminate useful data from those that are not [e.g. camera trap images, Chapter 11; (Tabak et al., 2019)], although accuracy may be different (e.g. lower) than the obtained with manual classification. These techniques can be applied: 1) in a computer where the data are stored; 2) in the cloud where the data can be uploaded; or 3) in an additional computing device physically close or embedded in the data collection device, which is known as edge computing (Hamilton, 2018). Edge computing is faster than processing the data on the cloud because there is no need to transmit the all the information to be analysed (which avoids energetic expense) and because cloud saturation is avoided (O'Brien, 2019). In the age of the Internet of Things and with the progressive implementation of 5G, a significant progress in edge computing is expected (Pan & McElhannon, 2018).

The development of specific algorithms for the detection and identification necessary to discriminate images (from camera traps or drones) or specific sounds (from bioacoustic sensors) requires high volumes of data for training to be effective (see details in the Chapter 11). In this regard, the multidisciplinary collaboration between computer scientists, engineers and conservationists; the development of data sharing platforms; and policies that favour these two, could contribute to these advances taking place faster. For example, the Conservation AI initiative aims to harness machine learning for various conservation projects (https://conservationai.co.uk/). While possibly still far from access for the conservation technology community, the advances of quantum computing (Arute et al., 2019; Harrow & Montanaro, 2017) are likely to produce a dramatic breakthrough in artificial intelligence and increase the speed of data analysis (Neven, 2019).

13.3 New technological trends

In this section I describe some technological advances that are currently revolutionizing other sectors but that still do not seem to have reached their full potential in conservation science - see also Allan et al. (2018) for a review.

13.3.1 Robots

Robots are machines controlled by computers that are used to perform jobs (Corke, 2011). They serve for different purposes, mainly aimed at saving efforts in routine industrial or domestic tasks or to work in environments that are too dangerous or of too difficult to access for humans. They are built from different materials (e.g. wood, metal, synthetics or living tissues); require power supply; and contain computer programming code that determines what to do, when and how to do it. Robots can have sensing and actuation capabilities. Sensing is acquired once a unit is equipped with the appropriate instruments (e.g. vision, acoustic, or touch sensors) and facilitate their interaction with the environment, humans and other robots. Actuation is performed in different ways, e.g. by rolling, walking, running, jumping, and manipulating objects with different levels of dexterity among others. Some perform mechanical tasks such as vacuuming, gripping, pounding or throwing. Despite robot sensing capabilities being applied across sectors, there are still few examples on robot acting capabilities used in conservation (Grémillet, Puech, Garçon, Boulinier, & Le Maho, 2012).

Drones constitute an example of robots that have been successfully integrated as conservation technology tools (Chapter 3). They are currently mainly used as flying cameras that collect images, but their potential to perform other robotic tasks has recently started to be explored for applications such as gathering water samples (Schwarzbach, Laiacker, Mulero-Pazmany, & Kondak, 2014); trap insects (Albo

Sanchez-Bedoya et al., 2013); obtain whale blow (Pirotta et al., 2017); collect data from bio-logged animals (Cliff, Fitch, Sukkarieh, Saunders, & Heinsohn, 2015; Dos Santos et al., 2015; Körner, Speck, Göktoğan, & Sukkarieh, 2010); record acoustic biotelemetry (Leonardo, Jensen, Coopmans, McKee, & Chen, 2013); intentionally direct animal movements (Penny, White, Scott, MacTavish, & Pernetta, 2019); air pollution monitoring (Satterlee, 2016); spread water and non-hazardous chemicals to reduce air pollution (Deck, 2019) and deploy sensors in areas of interest (Shih et al., 2015). Drones are also being used in other sectors performing tasks that could be potentially transferred to conservation research or management. For example, they are used in agriculture to spread fertilizers and pesticides (Kale, Khandagale, Gaikwad, Narve, & Gangal, 2015) and for mosquito control (Amenyo et al., 2014), which may have potential for invasive species management; in forestry for planting (US 9852644 B2, 2017), which could be applied to restoration tasks; for fishing and hunting (Hanna, 2015) which may contribute to wildlife captures in the conservation scenario; and for infrastructure manipulation (Acosta, de Cos, & Ollero, 2020) which could be useful for wildlife management and gathering samples from locations that are difficult to access.

Unmanned Ground Vehicles (UGVs) can be used similarly to drones but in terrestrial environments, for example to gather images or sounds; collect samples (Grémillet et al., 2012); gather data from marked; or for physically removing invasive species (Baskaran et al., 2017) and trash (Bogdon, 2018; Zapata-Impata, Shah, Platt, & Singh, 2018). Unmanned aquatic robots in all its variants (linked to a boat by a tether; remotely operated; or autonomous) and working at the surface or underwater, offer a new array of possibilities that has just recently started to be explored to study rivers, lakes and oceans, obtaining images and gathering samples (Steimle & Hall, 2006; Yuh, Marani, & Blidberg, 2011). There are other robots with innovative locomotion abilities. For example SlothBot (Notomista, Emam, & Egerstedt, 2019) that moves by switching between branching wires on a mesh, is designed for long-term environmental monitoring application, is solar powered, and energy efficient.

There are more futuristic application of robots, still far from being economically or practically feasible in conservation biology, but that present potential. The advances in the use of drones for delivering goods or medical equipment could be transferrable to transport equipment, unmanned ground vehicles or biological samples, which would support fieldwork in remote locations. Similarly, large unmanned ground vehicles can work as “mule field assistants” for logistical assistance (Airsource Military, 2014). Robots and smart wearables may also contribute to safety, for example helping disabled people to conduct fieldwork (e.g. 4*4 wheelchairs) or for self-transportation (e.g. hoverboards / flyboard air).

13.3.2 Social Networks, stream video platforms

Since 2000, data sharing has been primarily facilitated by social networks (e.g. Facebook, Instagram, Snapchat); websites dedicated to audio-visual contents (e.g. Youtube); an array of mobile phone apps (specific wildlife ones described in detail in Chapter 9); and messaging platforms (e.g. WhatsApp). The vast amount of information that users upload for various purposes, not necessarily related to science, may nevertheless have scientific interest for conservation. Posts, images and videos can be analysed to extract data from animals, plants or environmental features, to detect changes in the environment, and to study people's perception about conservation actions or topics. For example, Nekaris et al. (2013) analysed the comments and data posted on a viral YouTube video about slow lorises, a threatened and globally protected primates group. The webometric data allowed them to evaluate societal sentiments towards the species and served to identify a strong desire of people to have one of these animals as a pet, demonstrating the need for Web 2.0 sites to provide a mechanism that allows illegal animal material to be identified and policed. The access and exchange of information can also open new possibilities for local communities exposed to human-wildlife conflicts to manage natural resources and protect biodiversity. For example, Lewis, Baird, and Sorice (2016) documented how people from Masai rural communities in northern Tanzania, on the border of Tarangire National Park, use mobile phones to alert herders about the presence of potentially dangerous animals, which helps reducing the incidence and the severity of wildlife attacks.

Environmental authorities are increasingly investing resources in digital research to detect poaching networks, to locate where the activities occur in the field (e.g. via mobiles phones) and to collect evidence against offenders and consumers of wildlife derived products that are often sold online. For example, information shared in social networks (Di Minin, Fink, Hiippala, & Tenkanen, 2019; Di Minin, Fink, Tenkanen, & Hiippala, 2018) and the dark web (Harrison, Roberts, & Hernandez-Castro, 2016; Roberts & Hernandez-Castro, 2017) proved to be useful to detect illegal trade of wildlife products.

13.3.3 Virtual and augmented reality

Like with social media, the recent major advances in virtual reality (VR) and augmented reality (AR) contribute to disseminating conservation science. VR is characterized by the illusion of participation in a synthetic environment that relies on three-dimensional, stereoscopic, head-tracked displays, hand/body tracking, and binaural sound (Gigante, 1993). It is an immersive, multisensory experience commonly used for entertainment and educational purposes. Similarly, augmented reality supplements the real world with virtual (computer-generated) objects that appear to coexist in the same space as the real world (Krevelen & Poelman, 2010). While there are similarities between VR and AR, VR creates an artificial environment to inhabit, and AR simulates artificial objects in the real environment (marxenlabs, 2020). None of these two technological developments provide new data, but they can substantially change the way to visualize, contextualize and interact with remote data.

VR has been used to recreate Australian forests where experts are virtually immersed to assess suitable habitat was for koalas (*Phascolarctos cinereus*), which, in combination with data obtained by other means, contributed to species distribution modelling and conservation (Leigh et al., 2019). Virtual tourism, in which the system user can feel embedded in different scenarios - such as a savanna or a coral reef - serves for educational purposes, facilitating people to feel closer to nature and value it more. For example, the virtual reality (VR) application apeAPP VR, designed to be viewed in full, immersive 360 degrees (when paired with a Google Cardboard-style headset) offers immersive tours of great ape habitats. It allows to remotely explore protected areas around the world (e.g. Gashaka Gumti National Park in Nigeria, Tripa Peat Swamp in Indonesia) and to learn about ape species through maps, images, audios and other resources (Ape Alliance, 2020). Immersive virtual reality field trips also constitute a useful tool for environmental education and important social issues such as climate change (Markowitz, Laha, Perone, Pea, & Bailenson, 2018). Virtual reality can also potentially help scientists interact with remotely operated or remotely installed devices. For example, there are several VR software packages that help training drone pilots (DJI, 2020) and most drone systems can integrate VR headsets that serve to visualize the overflown area from the aircraft perspective in real time and to pilot the system according to what the pilot sees as captured by the drone frontal camera (first person view flight mode). It is not difficult to imagine a scenario in which scientists operate mobile aerial, terrestrial or aquatic robots deployed in remote locations using virtual reality tools.

AR scenarios are particularly useful to help conservation managers and decision makers to visualize environmental characteristics in the field and to better interpret the results of predictive models. For example, Danado et al. (2003) describe an AR project developed in the Parque das Nações and the Tagus Estuary (Lisbon, Portugal) for environmental management that provides geo-referenced information to the user and presents superimposing synthetic information over real images. The visualization includes water quality (using pollutant transport simulation models); superimposition of synthetic objects such as urban buildings and natural landscapes to visualize their characteristics and temporal evolution, and the projection of synthetic images that reveal the soil's composition at the user location. Augmented reality also helps students learn about wildlife protection. For example, Conserv-AR (Phipps et al., 2016) is a virtual and augmented reality mobile game that has been applied to enhance wildlife conservation at Murdoch University (Australia), specifically focusing on the Carnaby's Black Cockatoo (*Calyptorhynchus latirostris*), an endangered bird species of Western Australia. It takes the user on a field-trip where the player moves within a dynamic map towards waypoints, receives queries to find targets, visualizes three dimensional objects and text panels that contain environmental information, and interacts with game characters.

13.4 Integrating technologies

The integration of different technologies allows scientists to obtain information from different components of the ecosystem at matching spatio-temporal scales, which helps understanding ecological processes and managing environmental threats, leading to more effective conservation strategies (see a review in (Marvin et al., 2016). Conservation technology offers a range of tools that collect data from landscape to molecular scales: satellites-drones-camera traps, acoustic sensors- animal borne technologies-physiological sensors-field labs-eDNA. In this section, we review how the different available tools can be linked to increase the efficacy of data collection efforts for research and management, first with human intervention and then without it.

13.4.1. Combining conservation technologies with human intervention

There are several examples where combining different technologies served to address conservation questions. For example, Rodríguez et al. (2012) used biologgers to obtain precise locations of hunting movements of reintroduced lesser kestrels (*Falco naumanni*), and drones to replicate the trajectories made by the marked individuals, collecting high resolution aerial images that serve to characterize the habitat in quasi real time. While animal-borne technologies had been used before for habitat selection studies, in this case spatio-temporal resolution of habitat data were dramatically better than traditional means by e.g. satellite imagery. The combination of these two technologies allowed researchers to gather animal and habitat data at similar scales (temporal: hours; spatial: meters), which served to study short-term behavioural patterns in highly dynamic scenarios.

Technologies can also be physically integrated. For example, Wilson, Barr, and Zagorski (2017) attached acoustic sensors to drones to perform bird censuses. This allowed the researchers to work in areas that are difficult to access on-foot and helped reduce the biases produced by the observer presence and habitat coverage. Different receivers have also been integrated in drones to collect data from tagged animals (Desrochers et al. 2018; Saunders 2016; Tremblay et al. 2017). This combination facilitated to increase the quantity and quality of data, that otherwise relies on the personnel deployed in difficult-to-access terrain. In a recent review, Buxton et al. (2018) provide numerous examples on how pairing camera traps with acoustic sensors serves to evaluate wildlife abundance, distribution and behaviour across landscapes while monitoring human stressors at the same time. This technological combination turned out to be particularly useful to improve detection accuracy and helped to strengthen statistical inference at multiple survey scales.

The combination of different conservation technologies constitutes a valuable tool for the efficient management of protected areas and species (Marvin et al., 2016).

SMART systems, as described in Chapter 10, allow integrating, analyzing and visualizing data from different sources, such as rangers or remotely deployed data collection devices such as camera traps or bioacoustic sensors. For example, rhinoceros antipoaching can benefit from the combination of drones that provide aerial perspective; acoustic sensors that can detect gun-shots (González-Castano et al., 2009; Sarma & Baruah, 2015); motion sensors on fences that serve to detect unauthorized access (Cambron, Brode, Butler, & Olszewkski, 2015); camera traps to detect animals and humans; and animal-borne technologies to get real time locations of animals (Firmat Banzi, 2014; Kalmár et al., 2019; Kamminga, Ayele, Meratnia, & Havinga, 2018). The recent advances in artificial intelligence, such as machine learning, can facilitate the analyses of the vast amount of data collected from different sources, so that the end users are provided with the relevant analytics (see chapter 11).

The non-governmental organisation, Save the Elephants, works towards facilitating elephant coexistence with local communities in Kenya by combining GPS collars with geofencing to detect when marked elephants enter conflictive areas such as agricultural fields. Their personnel automatically receive messages on smartphones that accelerate them learning when and where to chase off problematic individuals to avoid further damage (Save the elephants, 2000).

13.4.2 Combining conservation technologies without human intervention: Wireless Sensor Networks and Internet of things

Internet of Things (IoT) is one of the most important areas of future technology (Atzori, Iera, & Morabito, 2010). It is gaining widespread attention from diverse fields such as logistics, transportation, health, safety, traffic management and city planning (Lee & Lee, 2015; Miorandi, Sicari, De Pellegrini, & Chlamtac, 2012; Zhao, Zheng, Dong, & Shao, 2013). IoT concept is defined as "a network of physical objects" (Patel & Patel, 2016). These physical objects are also referred to as "things" and should: 1) have a physical embodiment (e.g. machines, animals, plants or people); 2) be able to sense (i.e. sensors, e.g. temperature, light) and eventually also to perform actions (i.e. actuators; e.g. move); 3) be uniquely identifiable and addressable in a machine-readable way; 4) be embedded with processors or micro-controllers that allow data processing and communication (Atzori, Iera, & Morabito, 2017; Friedemann & Floerkemeir, 2010; Minerva, Biru, & Rotondi, 2015; Miorandi et al., 2012; Patel & Patel, 2016).

IoT is related and often overlaps with Wireless Sensor Networks (WSN). WSN are spatially distributed networks of autonomous sensors built with the objective of collecting physical or environmental data (e.g. temperature) in a certain area (Barrenetxea, Ingelrest, Schaefer, & Vetterli, 2008). IoT objectives are generally more complex than those of WSN and the "things" often work as actuators in order to achieve goals without human intervention (Minerva et al., 2015). Besides, in IoT the “things” have unique identifiers and are connected to internet, which does not necessarily apply to WSN (Minerva et al., 2015).

The main advantage of WSNs is that they allow collecting data with minimum power consumption, so the networks can work autonomously for long periods (months or years). The data collected by the network nodes are transmitted among them using short range connections in a smart way and then collected by a sink that forwards the data to the end user (e.g. via internet or long- range radio). Many IoT applications often relay on short range technologies such as Bluetooth, ZigBee or WiFi, or eventually, on long range ones such as cellular networks. Emerging low power wide area network (LP-WAN) technologies such as LoRa or Sigfox offer better coverage with low energy consumption (Ayele, Das, Meratnia, & Havinga, 2018). WSN can be customized in different ways so that data is sent to the end user on a schedule or when the results of local data processing indicate that an event of interest has taken place (Barrenetxea et al., 2008).

IoT - and generally WSN - contribute to wildlife conservation research in different ways (see a review about WSN in ecology in Porter et al. 2005; advanced sensors in ecology in Porter et al. 2009; and IoT in animal ecology in Guo et al. 2015). WSN are particularly useful to monitor large areas because numerous low-cost sensors can be deployed and connected with low power consumption, allowing researchers to detect changes in the environment in real time (Othman & Shazali, 2012; Porter et al., 2005, 2009). Sensors gather data about physical-chemical parameters of interest, such as wind, humidity and temperature, or they can be combined with wildlife data collection devices remotely deployed such as camera traps or acoustic sensors (Porter et al., 2005). WSNs have been used in research to support remote field-stations (Porter et al., 2009), conduct climate change studies (Fang et al., 2014), monitor wetlands (Xiaoying & Huanyan, 2011), detect changes in forests (Othman & Shazali, 2012), and monitor noise pollution (Santini, Ostermaier, & Vitaletti, 2008).

WSN constitute a valuable tool for integrating animal-borne technologies. The integration of wildlife tags in WSNs enables data to be transmitted in an efficient way among the network nodes. In this way, WSNs conserve power, consequently increasing the autonomy and range of the tags, the time they can work without human intervention. Another advantage of WSN is that once deployed (for example, in a national park) WSN infrastructure can be used for diverse projects, favouring reliable and inexpensive data collection (Porter et al., 2005). One of the first studies of WSN applied for animal monitoring was the ZebraNet project (Juang et al., 2002; Zhang, Sadler, Lyon, & Martonosi, 2004), where zebras in Masai Mara, Kenya were marked with transmitters in a WSN that allowed researchers to investigate their movements and interactions. WSN and IoT are often used for monitoring livestock and often combined with static sensors that record environmental variables (e.g. about climate) or with satellite images that allow to study cattle movements and their interactions with the landscape (Handcock et al., 2009; McIntosh et al., 2020; Stojkoska, Bogatinoska, Scheepers, & Malekian, 2018; Wark et al., 2007).

As mentioned, WSN constitute a useful solution to monitor large and even small animals that can carry tags with limited weight. They have been used to conduct research about the behaviour and spatial ecology of the Manx Shearwater (*Puffinus puffinus*) in Skomer Island, a UK National Nature Reserve (Naumowicz et al., 2008); for tracking and behavior recognition of marked pigeons (Liu et al. 2017) and a wireless network of acoustic recorders aided to study yellow-bellied marmots (*Marmota flaviventris*) (Ali et al., 2009). They have also been used to monitor bats and birds with low cost tags based on IoT system-on-chips using different communications modes (Toledo, Orchan, Shohami, Charter, & Nathan, 2018).

There are several open source options that allow conservationists to incorporate IoT solutions at a lower cost than commercial ones. For example, IoT Mataki project offers a wirelessly enabled, low cost and readily programmable tag that was developed by the Zoological Society London, University College London and Microsoft Research (Institute of Zoology. ZSL, 2020). Arribada's Horizon platform provides the building blocks necessary to develop low-cost wireless sensors and biologging tags. It has a modular design that focuses on the provision of a central control board that breaks out popular input / output connectivity (SPI / I2C) that enables the researchers to use their own proprietary sensors or payloads (Shuttleworth Foundation, 2020).

WSNs are useful tools to collect, transmit and store vast volumes of environmental data that can be used to improve wildlife management (Jones, Warburton, Carver, & Carver, 2015). For example, organizing surveillance static and mobile sensors (e.g. drones) for detecting illegal activities that can affect endangered species in WSN optimizes power use and allows transmitting the information via local networks or internet in real time to the managers and rangers so that they can react on time (Kamminga et al., 2018; SMART, 2020). IoT can also contribute in managing other human-wildlife conflicts scenarios that require fast response. For example, the smart integration of sensors (cameras, motion sensors) installed around infrastructures and tags attached to animals has been suggested to divert animal intrusions in agricultural land (Bapat, Kale, Shinde, Deshpande, & Shaligram, 2017) and to avoid accidents along train lines and roads (Bhagyashree, Sonal Singh, Kiran, & Padmini, 2019; Ramkumar & Sanjoy, 2015). When the sensors detect animals in a dangerous proximity to the infrastructures, the network can provide early warning to drivers through smart phones or LED displays on the roads, or communicate directly to the vehicles making them stop to avoid accidents (Bhagyashree et al., 2019; Kurain, Poojasree, & Priyadharrshini, 2018; Mohanasundaram & Dane, 2017; Ramkumar & Sanjoy, 2015).

Most of the current IoT applications in conservation science exploit the idea that sensors are connected to each other sharing information, but IoT possibilities go far beyond this. The connected objects can also perform actions according to the information received from another sensor. This idea is exhibited in swarm theory, where drones or other autonomous vehicles can move in self organized groups to acquire environmental or wildlife data and transfer the information to each other and to the end user in more efficient ways than if they operated without coordination (Allan et al., 2018). For example, long autonomy solar powered drone swarms can act as data mules uploading raw or preprocessed (by edge computing) data from camera traps, acoustic recorders, or other remotely installed devices. In Planet project (Planet consortium, 2013), an IoT platform combining static and mobile objects was deployed in Doñana National Park (Spain) for environmental pollution monitoring. The static sensors were integrated in environmental stations that collected data about water quality (among other variables) and the mobile sensors were fix-wing and rotary-wing drones and UGVs. A simulated abnormal value detected in the water by a static sensor triggered the flight of the drone, which in turn performed several actions: 1) gather images to visually investigate the occurrence of a pollution event; 2) drop specific sensors on the affected area to gather additional information on the water pollutants; 3) collect water samples that could be analyzed in a lab; and 4) deploy a UGV equipped with video cameras for a closer inspection of the affected ground (Marrón, Shih, Figura, Fu, & Soleymani, 2011; C.-Y. Shih et al., 2014; C. Shih et al., 2015).

In summary, IoT and WSNs formed by heterogeneous static and mobile sensors facilitate collecting and transmitting data in a power efficient way, allowing scientists to monitor wildlife, large natural areas, detect environmental changes, and potentially react to them in autonomous way.

13.5 Problems and solutions in conservation technology

Conservation technologies substantially contribute to wildlife research and management, allowing species monitoring, habitat characterization, environmental change detection, and conservation threat exposure (Lahoz-Monfort et al., 2019; Pimm et al., 2015). However, the use of any technology is often a trade-off between risks, costs, data acquisition/processing, and issues related to logistics (Marvin et al., 2016). For example, some of the technological integration failures can result from short-term motivations to use technology in the first instance (e.g. to exploit the novelty or to publish the feasibility of an idea - Joppa 2015); or to an unfounded excess of confidence on the tool to produce the desired results (the technology “hype”(Arts, van der Wal, & Adams, 2015; Lahoz-Monfort et al., 2019). These problems could be addressed promoting more communication with other users, providers and developers that may help to get a realistic idea about the actual possibilities, timeframe, training period, and total costs that should be invested for obtaining satisfactory results with a particular technology (Lahoz-Monfort et al. 2019, also e.g. see Chapter 11).

It is critical for conservationists to spend time familiarizing themselves with the new technologies (Marvin et al., 2016), whose learning curve varies among the different devices. As technologies are integrated into fieldwork, personnel needs to have specialized skills, which has led to an increasing training offer by a range of companies and academic institutions via short specific courses (e.g. Camera trapping from Wildlabs.net; Environmental DNA (eDNA) Methods from Natural Resources Training Group, Canada), or long terms programs that cover several technologies (e.g. Wildlife Conservation Technology MSc from Liverpool John Moores University, UK).

Some authors have raised concern regarding the possible negative implications that conservation technology may have for nature and humans (Arts et al., 2015). Poachers or illegal fishermen/loggers can indeed buy cameras or drones for illicit purposes, and wildlife traffickers can access public apps or social networks to get information on the locations of individuals of endangered species (See chapter 12, e.g. Duffy et al. 2018; Sandbrook 2015). While this misuse of the technology is difficult - if not impossible – to control, there are some initiatives to address them, such as enforcing data confidentiality, discouraging the publication of locations of sensitive species, and adopting anti-hacking strategies that are aimed to mitigate these practices (Pimm et al., 2015). The effects of using surveillance technology (e.g. camera traps, drones, acoustic sensors) to gather information about people's activities (intentionally or unintentionally) continue to be discussed. Chapter 12 summarizes some of the major concerns on data privacy, civil liberties and freedom, which are particularly concerning for local communities that may develop mistrust towards conservationists (Duffy, 2015)

Some of the main barriers to applying conservation technology are related to the difficulties that developers face during innovation. The sometimes short-term focus of research projects often leads to designs and prototypes that rarely scale-up to become commercial and available for a broader conservation community (Joppa, 2015; Lahoz-Monfort et al., 2019). This is exacerbated by a range of problems such as the lack of financial sustainability in the long term or miscalculations about the potential market for the developed product (Iacona et al., 2019; Lahoz-Monfort et al., 2019). As an alternative to traditional business models, open source software platforms, DIY (Do It Yourself) initiatives, and participatory models are gaining popularity among users and developers (Berger-Tal & Lahoz-Monfort, 2018; Pimm et al., 2015). This networked science facilitates collaboration between researchers and engineers and may allow the broader population to access technology at lower costs (Pimm et al., 2015). This contributes to the democratization of progress, which is also important for conservation because low income countries that host high biodiversity levels and short budgeted research teams have still limited access to some of these tools (Conway, 1986). Other solutions that have been suggested to promote open access collaboration include the "hackathons" and "codefests", where interdisciplinary experts meet to design novel technical solutions; prizes and competitions that aim to recognize and encourage the efforts of those actors to advance in specific conservation challenges (Pimm et al., 2015).

There is a general consensus among the conservation technology community that multidisciplinary collaboration and partnership between researchers, practitioners and technologists is good for the field (Arts et al., 2015; Joppa, 2015; Marvin et al., 2016). This should include not only those working in conservation, but also stakeholders from other fields (e.g. agriculture, health) that may have compatible interests (Allan et al., 2018). These synergies (1) help the development and implementation of solutions for specific needs, (2) boost the sharing of ideas and resources, (3) encourage market developments via business processes, and (4) the sustainability of resulting solutions (Joppa, 2015). For this purpose, several initiatives have been created (e.g. The Conservation Technology Working Group of the Society for Conservation Biology; Wildlabs.net; see Berger-Tal and Lahoz-Monfort 2018 for a detailed list).

Conservation technology is poised to revolutionise the way biologists collect data, the speed and extend of complex analyses, and the means to feed critical results to stakeholders in time to address critical issues confronting wildlife. As often happens with innovation, the speed of the technology often exceeds the rules and ethical framework that guide its implementation, which can have knock on effects for society (privacy violations, etc). Nonetheless, the preceding chapters make clear the diverse, widespread, and flexible use of these developments and their role in the present and future efforts to conservation wildlife.

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