The Smart Forest Conundrum: Contextualizing Pitfalls of Sensors and AI in Conservation Science for Tropical Forests

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Abstract

The term 'smart forest' is not yet common, but the proliferation of sensors, algorithms, and technocentric thinking in conservation, as in most other aspects of our lives, suggests we are at the brink of this evolution. While there has been some critical discussion about the value of using smart technology in conservation, a holistic discussion about the broader technological, social, and economic interactions involved with using big data, sensors, artificial intelligence, and global corporations is largely missing. Here, we explore the pitfalls that are useful to consider as forests are gradually converted to technological sites of data production for optimized biodiversity conservation and are consequently incorporated in the digital economy. We consider who are the enablers of the technologically enhanced forests and how the gradual operationalization of smart forests will impact the traditional stakeholders of conservation. We also look at the implications of carpeting forests with sensors and the type of questions that will be encouraged. To contextualize our arguments, we provide examples from our work in Kibale National Park, Uganda which hosts the one of the longest continuously running research field station in Africa.

Keywords

sensors, monitoring technologies, poaching, protected area, Kibale National Park, drones, camera-traps, remote sensing, AI

Introduction

Data is the foundational form of capital in the digital economy, underpinning the technological transformation of everyday objects and environments to make them 'smart' (Kitchin, 2014). This is evidenced by the flurry of new terminology with the 'smart' prefix, such as, smart cities and smart homes. The term 'smart' is often used as a shorthand to indicate the presence of sensors which generate a constant stream of data and possibly make some autonomous decisions based on the patterns in the data. Collection and circulation of data is a basic premise of data currency driving corporations to devise new ways of extracting all data, from all sources, by any means possible (Fourcade & Healy, 2017). The transformation of data to a new form of currency means that data by itself is valuable and value-creating (Arvidsson, 2016; Roderick, 2014; Srnicek, 2017). Data is collected with the belief that it will have use, and thus value, at some point in time, if not today.

In the digital economy, data is a capital which is worth finding, creating, accumulating, and trading. Capitalism in this new digital form is also always looking for new places and domains to exploit for data capture (Harvey, 2014). A potential, lucrative domain involves tropical forests. Covering 7% of the world's land

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surface, tropical forests account for 60% of the world's biodiversity (Bradshaw et al., 2009). These forests are increasingly threatened. Less than half of the world's tropical forests remain (Pimm et al., 2014) and between 2000 and 2012, globally forest were being lost at 3% annually (Hansen et al., 2013). The imperative of protecting the remaining biodiversity presents the perfect justification to 'optimize' biodiversity conservation by using smart sensors to collect data and automate processes. The premise is that with a constant stream of multidimensional data and autonomous decision making, the solutions are limited only by our imagination. As the narrative of a conservation crisis needing technological salvation gains pace, there is simultaneously a growing concern about 'techno-fix' thinking in conservation (Arts et al., 2015; Gabrys, 2016, 2020; Joppa, 2015). Current trends of creating technologized sites of data production and their purported advantages in increasing management efficiency is reflected in the conservation literature with the trickling stream of articles with variations of the moniker 'smart forest' (Bakker & Ritts, 2018; Gabrys, 2020; Lyubenova et al., 2015). As with all technological creations there is the potential for large gains to be made for conservation, but there are also dangers. How the balance between gains and losses will play out for conservation, will depend on how programs implement the use of technology and consider the value of alternatives.

In this paper, we focus on the pitfalls of the increased use of sensors and algorithms for conservation of tropical forests which are characterized by dense vegetation and are often bordered by human settlements. While the gaze of the digital economy on biodiversity conservation have been fleeting for now, there is little doubt it will gain traction. Currently, technological implementations are bottom-up, led mostly by researchers, rather than top down where they are mandated by governments, institutions, and funding organizations. However, the enamor of optimization has driven calls for investment opportunities by entities, such as the World Bank, to coax the remaining biodiversity to be more productive (Tembon, 2019). Thus, a more critical discussion is warranted that centers smart forests amongst the larger ecosystem of digital economy and the neo-liberal stresses of optimization and privatization.

While there are real advantages for conservation in acquiring more data and automating processes, critical considerations of how the data is collected, stored, and analyzed and its impacts from ecological, economic, social, and policy perspectives are largely lacking. To situate smart tropical forests in the larger digital economy we look at three questions; What are the impacts of placing smart technology in forests in terms of conservation science research? Who are likely to be the drivers of this techno-movement? And, what are the

implications for the traditional stakeholders of conservation which include local communities, researchers, and governments? We provide examples from our field site in Kibale National Park, Uganda (hereafter Kibale) to contextualize the arguments. Kibale is one of the longest continuously running forest research field station in Africa and provides a good case study as research protocols and costs have been established over decades and we have worked on forest conservation in the park for over 30 years. Our focus is on contextualizing the socio-economic environment which influences techno-centric smart forest interventions and identifying the actors involved in this transformation where use of sensors is widespread, and algorithms are entrusted with decision making. We provide reflections to guide tropical forest conservation researchers and institutions who are contemplating increased deployment of sensors.

The Cost Effectiveness of Sensors in Conservation Science

The use of sensors in conservation science is not new. Common examples include satellites, weather stations, drones, and camera traps. The key feature for these 'traditional' technological deployments is that the data processing and decision making is done with a human in the loop and at a pace that allows time for deliberation. Also, sensors such as weather stations and camera traps are placed discretely inside the forest to collect specific data obtained when the scientist is not present. Both these characteristics are evolving as sensors have more diverse functions and are smarter. Furthermore, with smart sensors, the analysis and decision-making can be delegated to black box algorithms, giving rise to 'conservation by algorithm'(Adams, 2019). An example of this is using AI to identify species or individuals based on camera traps; a process that can evaluate images in a fraction of the time a human observer can (Guo et al., 2020; Norouzzadeh et al., 2018). In this section, we chart how 'traditional' sensors and their data are being appropriated for smart forests.

One of the main challenges for researchers and managers is to develop cost-efficient approaches for ecological monitoring (Newey et al., 2015; Yoccoz et al., 2001). In high-income countries, where the salaries of researchers and technicians are high, this challenge has led to advocating for the use of sensors. However, this reasoning does not necessarily apply to tropical forests which predominantly occur in low-income countries and have high population densities around the forests. Here it is possible to provide local people with good salaries at a fraction of the cost of what it would be in high-income countries. From this perspective, sensors with built-in planned obsolescent and high maintenance costs, become an expensive

strategy. The cost of sending a technician to a remote tropical forest site for a minor adjustment or repair, will often be an order of magnitude higher in low-income countries and thus it can be prohibitive.

It is important that the academic community does not adopt a perspective that the only way to obtain high-quality data to address conservation questions is to use the approaches that work in high-income or high-tech countries. For example, camera traps have become a popular means to estimate density, species richness, and occupancy and detection rates (Kays et al., 2020; Linkie et al., 2013; O'Connell et al., 2011). A simpler, but much more labor-intensive way to answer many of the same questions that camera traps are used for, are tracking stations (Keeping & Pelletier, 2014). We estimated the relative costs of a camera trap versus a tracking station study using salary costs from Kibale. Using the number of cameras recommended for detecting rare species (Kays et al., 2020) and selecting a mid-range camera (Newey et al., 2015) this approach would be six times more expensive than the labor-intensive tracking station method.

Additionally, with respect to the quality of information collected or decisions made, people tend to trust machines even if the error rate is comparable or even higher than humans (Merritt et al., 2013). Thus, the implicit assumption that smart sensors will be more accurate, cost-efficient, and objective are debatable. The detriments caused by trusting autonomous decisions can be more severe than random or systematic errors associated with instruments.

Sensors are efficient at monitoring what they are designed to sense, but they may not provide needed context. For example, drones can monitor if canopy trees flower and fruit, but they will not record when small seeds are aborted. Someone collecting data from under a tree will note such events. Similarly, by using camera traps one could document a population decline in a species, but not be able to document the cause. If the cause was a disease outbreak, a person monitoring tracking stations would smell the rotting carcasses and likely identify the cause.

Sensors can stress animals. This is counter to the goals of conservation efforts as stress can negatively affect reproduction (Ziegler et al., 1995). For example, drones have been documented to cause physiological stress to mammals and birds (Ditmer et al., 2015; Rebolo-Ifrán et al., 2019; Vas et al., 2015). Humans perceive camera traps as being silent and unnoticeable, but there is clear evidence that they can be detected by animals (Meek et al., 2014). A variety of birds and mammals exhibited behaviors indicating they notice camera traps (Meek et al., 2016; Séquin et al., 2003). Thus, the possibility exists that camera traps may stress some species and provide data about stress behavior rather than about their natural behavior. Consequently, as algorithms are trained on camera trap images, the patterns the systems learn are biased.

There are many situations where sensors can record information needed for tropical forest conservation that a human observer cannot obtain or that it would be impractical for people to collect. Sensors can detect phenomenon that are difficult to detect by human senses (e.g., monitoring elephant calls (Garstang, 2004; Wrege et al., 2017)) and can collect the data 24 hours a day (e.g., to determine feeding visitation of nocturnal frugivores (Rivas-Romero & Soto-Shoender, 2015)). Sensors can also provide data that would be impossible for people to collect. For example, if information is needed on the behavior and range use of animals that avoid human observers or range over areas too large for people to monitor, animals can be captured and telemetry equipment can be attached to them (e.g., the home range of a honey badger encompasses hundreds of km^2 (Begg et al., 2005) and in the forest these animals are very secretive). Such telemetry equipment can also monitor data that people cannot record (e.g., heart rate (Dechmann et al., 2011), body temperature (Marvin et al., 2016)). Another example is satellite technology, which can be used to assess forest dynamics across the range of electromagnetic spectrum which is much broader than what can be sensed by humans. Productivity and carbon stocks can be assessed and monitored on large spatial scales that are well beyond what is possible using traditional methods (Goetz et al., 2009; Hansen et al., 2013). Drones are gaining popularity for ecological and conservation and can be used to assess the abundance of canopy gaps or the presence of chimpanzee nests over large areas (Bonnin et al., 2018; Getzin et al., 2012) or describing the phenology of identifiable trees across a landscape (Park et al., 2019). The use of lidar from drones is a particularly promising technology to assess habitat structure and estimate biodiversity (Simonson et al., 2014).

The Actors Enabling the Technological Drive

The significant investments required to design, build, deploy, and maintain the infrastructure underlying smart environments has put corporations in the driving seat of the digital economy. This in turn has given tech monopolies unprecedented influence in private, social, political, and economic spheres (Kang & McCabe, 2020). Consequently, 'smart' environments, have been driven by a corporate-led free-market blueprint. The lure of capturing as much data capital as possible with the hope of deriving value from it has proven to be of interest for tech corporations. As the primary provider

of infrastructure, tech corporations are "driven by the perpetual cycle of capital accumulation, which in turn drives capital to construct and rely upon a universe in which everything is made of data" (Sadowski, 2019). Driven by the extraction imperative, the smart forests also represent a hitherto untapped data domain. Tropical forests provide a particularly lucrative environment as they are often bordered by people who have thus far not been a part of the digital economy. Thus, smart forests brings into its fold not only the forest, but also the surrounding communities. While the push for smart forests provides an impetus to expand telecommunication infrastructure, from the business perspective, it is also a unique opportunity to derive more and new types of behavior data, such as, human-forest interactions.

The tech infrastructure required to operationalize smart forests are mostly provided by tech corporations putting them in the driving seat this frontier in conservation. As the capabilities of sensors and algorithms are increasing, so is the potential for corporations to influence conservation science and policy. This growing interest is illustrated by the increase in the number of grants supported by corporations to employ new technological solutions in biodiversity conservation (Gabrys, 2020; https://www.microsoft.com/en-us/ai/ai-for-earth-grants). Ideologues surrounding automation, optimization, and securitization of spaces common in smart environments are also manifesting themselves in the conservation dialogue as forests are increasingly perceived as data infrastructure (Gabrys, 2020).

While there has been previous engagement of corporations with conservation issues, they have primarily been in the form of philanthropic activities or social impact investments. The untapped data source of forests potentially provides an answer to the question, 'What does nature conservation offer as motivation for the technology industry to get seriously involved in building tools to conserve nature?' (Joppa, 2015). While the intentions of building smart forests may be well meaning, there will be consequences in terms of the conflicts in goals and values between various stakeholders, similar to what have been witnessed in the smart cities (Calzada, 2020). Thus, while corporations engage in philanthropic activities, their primary business relies upon profits from their products and services. Thus, smart forest introduces a new actor, corporations, to the equation which thus far primarily involved local communities, non-profits, researchers, and governments.

As a result, it is important for existing stakeholders to carefully evaluate if the information gained through smart forest implementations is worth the cost. This evaluation should consider the cost to maintain and run the sensor system in remote tropical forests and to upgrade the sensors and software as new versions become available. Project abandonment, even when the project is backed by large corporations is also not unprecedented. For example, Google affiliated Sidewalks lab abandoned visions to transform Toronto's waterfront into a smart city after years of planning (Leyland, 2020). Thus, comprehensive project sustainability evaluation frameworks need to be developed as the consequences of sensor abandonment in the forest can have significant impacts on biodiversity. It should also consider social costs and lost opportunity costs as funds could be used in other ways.

In the techno-fix view, technology is perceived as a panacea with incredible agency to solve social and environmental problems (Abdelnour, 2015; Huesemann & Huesemann, 2011; Morozov, 2013). Consequently, in the face of prolonged budgetary cuts to environmental funding, it is easy for tech companies or government agencies to call for technological interventions to overcome the impacts of environmental austerity. For example, rather than measuring carbon stocks, forest productivity, or food availability through tree measurements, calls are put forward to assess these variables using indices derived from satellite imagery. Verifying these indices accurately portray the variable of interest must be done prior to their adoption, as without proper contextual adjustments, some indices have been shown to be imprecise (Gautam et al., 2019). While technological interventions in the name of austerity can, when adequately tested, fulfil the needs of environmental monitoring, it undercuts the aims of poverty alleviation and involvement of local communities in conservation and may exacerbate marginalization (Kull et al., 2007; Morrissey, 2012). Instead, it adopts a neo-liberal perspective that involvement of private stakeholders will optimize the use of economic resources and provide favourable outcomes, setting in motion lobbying efforts for further austerity measures which in turn benefit the private enterprises (Fletcher et al., 2014).

Further, the lack of telecommunication and electricity infrastructure in many tropical forests will make the smart forest implementations challenging. However, this will likely be seen as an opportunity by corporations. For example, Microsoft has developed a modular datacenter capable of quick deployment in areas with adverse condition and haphazard communication infrastructure (Karagounis, 2020). While it can be argued that the development of such infrastructure can help local areas, it is unlikely that local communities can afford to use or maintain it without institutional support from local and national governments. On the other hand, implementing smart forest opens the opportunity to build capacity in the local communities to run and maintain the technological infrastructure thus accelerating and supplementing government initiatives. Hence, the opportunities should not be overlooked without consideration for the sake of tradition. There is a balancing

act required to ensure that we do not end up with 'smart' forests surrounded by tech deprived communities or with scenarios where the tech becomes too pervasive and its side effects, such as high-power electricity lights and sounds, interferes with the flora and fauna.

A final consideration with respect to the enablers of smart forests is that the technology developed in the western world is often ported over to the rest of the world with little regard for suitability in terms of application, assumptions encoded in the systems, and consideration of foreign economies and culture. As a result, there is growing concern about 'algorithmic colonization' (Birhane, 2020). Even though data-driven AI approaches are often perceived as objective, researchers have shown that implicit bias is encoded in the system and present in the datasets used to train the algorithms (Howard & Borenstein, 2018). These biases can lead to a slew of problems including implications for communities and incorrect ecological inferences (Galaz & Mouazen, 2017). Thus, it is important to reflect upon who builds the system, where, using what datasets, and for what purpose.

Data Implications for Conservation Science

In the digital economy, data is money. In the race to collect more data with the hope that they will be useful in the future, it is important to consider whether the data derived from smart forests will be sufficiently reliable to use in informing of conservation plans. For example, the use of AI-based species identification is increasingly common (Guo et al., 2020; Joly et al., 2018). AI systems rely on data to make decisions and drawing on large data sources increases their pattern learning ability. Drawing on existing data sources, such algorithms, can misidentify rare species or those not thought to be in an area (Wearn et al., 2019). In conservation, rare events are extremely important. Even though sensors can monitor situations continuously they rely on algorithms trained on existing datasets to match patterns and make decisions. Thus, when a new species (for the dataset/algorithm) is encountered, the algorithm can wrongly categorize them. In such situations, regular human monitoring and retraining using updated datasets is needed. Similarly, recent research suggests that even when deploying many camera traps in a small area, detection and capture rates are highly variable across space and time (Kolowski et al., 2021). This suggest camera trap data can be unreliable to address many conservation questions. Thus, while sensors are useful for detecting species that avoid human detection, over-reliance on sensors and algorithms could shift the focus away from ecologically important

events which require scientists to spend considerable field time to questions that are easily quantifiable. Further, use of sensors also creates an imperative to collect as much data as possible before framing clear questions (Succi & Coveney, 2019). However, well framed questions backed by small, purposefully collected datasets can help answer important questions (Faraway & Augustin, 2018; Xu et al., 2020).

Data does not stand on its own and needs to be contextualized to make it useful. This challenges the notion that unbridled data flow will lead to a situation in which our imaginations, rather than data and technology, will set the limits for solutions and scientific insights. People who work with datasets do not perceive data to be pliable for a variety of scenarios. Instead, they perceive data as something crafted for a specific task in a specific context (Madsen, 2018). Thus, data, regardless of the source needs to be put into context, analyzed, and narrated by the appropriate entities to be useful (Dourish & Gómez, 2018). Without careful planning, curation, and contextualization; data keeps accumulating in data stores and cannot be used most appropriately. For conservation planning, it often takes considerable effort and time in the field, interacting with the local communities, to contextualize data. For example, spikes in poaching incidents despite conservation efforts may point to lack of foresight in the overall conservation plans which is achieving the aim of increasing wealth for local communities, but not making available alternate desirable nutrition sources in the vicinity resulting in bushmeat hunting (Bortolamiol et al., Submitted).

A series of concerns are also associated with data security. Sensors placed within the forest for tracking animal, habitat quality, or environmental activity to aid in conservation can provide valuable information to poachers. Global trade in wild animals and plants is worth up to $350 billion annually (Sosnowski et al., 2019) and illegal wildlife trade has become the fourth largest international organized crime (Wasser et al., 2015). For example, since 2007, illegal ivory trade has been estimated to have doubled (Bennett, 2015) and forest elephant populations declined by 62% between 2002 and 2011 (Maisels et al., 2013). The data collected from sensors used by conservation scientists is valuable and attempts will be made to gain access to them. In some cases, the mere presence of sensors may signal areas of importance. This problem will be exacerbated with internet-connected sensors. These data streams and data stores can be hacked by the cartels who coordinate large scale illegal wildlife trade. Illegal wildlife trade is rife on the internet and getting access to fine-grained ground level data will bolster the market (Xiao & Xu, 2016).

Another important question that should be asked by all actors is, who will bear the cost for data collection,

proofing, and metadata organization, in addition to the costs associated with sensor maintenance and upgrading? Currently, most efforts are funded by researchers or conservation agencies, with governments from countries with tropical forests often viewing the sensors and associated data to be luxuries that they cannot afford as funding is often insufficient for needed day-to-day activities (Charles Tumwesigye - Uganda Wildlife Authority personal communications). This is not a desirable place for the field to be in as researchers and NGOs are typically supported by short-term grants and the value of using sensors is often derived from collecting long-term data.

Users should be concerned about the general willingness to share information, particularly if it is perceived by the people who purchase the sensors and pay for their establishment that others are unfairly profiting from their efforts. Setting-up central data repositories are challenging given the cost and complexity involved in collating and indexing the wide variety of datasets. For example, despite efforts to share bioinformatic data (https://www.coalition-s.org/), little data sharing has occurred (Arts et al., 2015). On the other hand, Movebank (www.movebank.org) has seen greater uptake and host movement data from a wide variety of sensors. In the absence of a central open data repository, data is locked inside silos negating the advantages of algorithms to gain insights based on mining large data repositories (Bakker & Ritts, 2018). If the corporations collecting and storing the data, such as is done with some areal imagery, it may be that the data will be locked behind paywalls, if made available at all. Scientists may have to buy access to the data, most probably in the form of subscriptions or a pay-per-use model, similar to accessing journal articles. However, any data sharing by corporations is unlikely at all given the secrecy in which algorithms and data is shrouded in other aspects of the digital economy (O'Neil, 2016; Pasquale, 2015). Thus, data ownership and custodianship are significant barriers to achieving a future where data-driven decisions are egalitarian.

Impacts on Local Communities

In addition to the already mentioned benefit provided by the smart forest movement of building infrastructure and collecting new forms of dataset, there are other opportunities that can become available if carefully plan and implemented. For example, to ensure scalability, maintainability, affordability, and inter-operability, open-source hardware and software can be developed and adopted to operationalize smart forests. This also opens the possibility of developing highly skilled personnel in the local communities who can take stewardship of the projects. However, the guidelines and best practices

should be debated, discussed with local communities, and set forth as the risks of improper implementation and data misuse are a significant concern.

With all conservation projects, it is important that the hard-earned funds be spent in a fashion that best facilitates both science and conservation. When conservation dollars are spent on sensors, funds are going to corporations, typically in high-income countries. In contrast, when a local villager living close to the conservation efforts is hired to collect data, funds go to the community and engender a positive attitude towards conservation efforts as it ameliorates some of the negative impacts of living next to protected forests (Kirumira et al., 2019; Sarkar et al., 2019).

If researchers adopt the perspective that high-tech approaches are the only way to get high quality data, this will result in local community members currently employed to collect data losing their jobs to sensors. Even if local employees are trained in the use of high-tech approaches (e.g., camera traps for density estimates, drones for phenology monitoring) by their very nature these technologies require less field time and thus renumerations to the community will decline. Thus, unless alternatives sources of employment are provided, years of progress in providing conservation-based employment for the local communities can be lost. Conservation calls for human involvement to build community trust and efforts benefit from positive relationships with affected communities. It takes years and perhaps decades for conservation scientists to gain community trust. If employing sensors means that the scientist will be in the field for less time, it will hinder conservation efforts. Furthermore, training students in conservation practice involves education in both the biological and social perspectives. This requires understanding the local community's culture, needs, and desires, which takes time in the field. One could argue that using sensors will provide researchers more time to interact with the community, but this has to be deliberate choice as with the use of sensors there is an incentive for researchers spend less time in the field and more time at their home universities. If care is not taken, there is a risk of 'deskilling' both conservation and natural history as we rely on sensors to collect data needed to address narrowly defined questions.

In current implementations of technocentric thinking in conservation, consultations and opt-ins from the community are largely missing. As conservation management get bound up in black boxes and controlled remotely, it can lead to situations where the people who are implementing activities are not acquainted with the ground realities. If not carefully managed, this can result in rigid, formal, and top-down management of conservation with little local accountability increasing government and corporate power and control (Barns

et al., 2017; Gabrys, 2020; Shelton & Lodato, 2019). Thus, for successful implementation consultations, opt-ins, and knowledge exchange are required from all stake holders including rangers, forest officials, and communities. These issues are in addition to the diversion of conservation funds from local communities mentioned above. Thus, unless carefully coordinated, smart forests have the potential to reverse the decades of efforts put in to make conservation management plans equitable for local communities. If researchers do not spend time in the community, there is the real risk that the community will not understand why some scientists intervene to make their life harder, while protecting animals. In early years of setting up the research field station in Kibale (1980s), communication with the local community was limited and the community thought that researchers were prospecting for gold. Because why else would they spend so much time in the forest and not leave with visible goods.

Ensuring security is one of the dominant arguments put forward in support of smart cities (Vanolo, 2014; Wiig, 2018). In fact, the data extraction imperative of the digital economy makes surveillance a central activity (Zuboff, 2015). Similarly, deployment of surveillance technology is emerging as a central concept in tech-moderated conservation (Adams, 2019; Sandbrook, 2015). Having protected areas that are managed to the degree where fires can be quickly discovered from satellites, problem animals can be monitored so that when they approach the boundary steps can be taken to prevent human-wildlife conflict, and patrol efforts can be spatially tracked is of great conservation value and is being implemented (https://earthranger.com/, Xu et al., 2020). This sort of information can be made available to managers in real-time and can enhance security. In a situation where, managers are trying to protect extremely endangered species, the monitoring systems are donated, community consultation is done, and training is maintained, such efforts will be valuable. These measures represent important positive advances, but a great deal depends how they are implemented

As securing a protected area becomes a primary concern, local communities may be negatively impacted by this militant protection of forests (Adams, 2019; Sandbrook et al., 2018). While the aforementioned security system serves a range of conservation purposes, systems explicitly built to detect and punish transgressors exacerbate the militant approach to protection and alienates the communities (e.g. thermal and infrared camera and software system to detect people crossing a national park boundary developed by World Wide Fund for Nature and Google). Such militarization of conservation has been termed 'War on Poaching' or 'Green Violence' to legitimize the use of force on a common enemy framed as the 'poacher' (Büscher & Ramutsindela, 2016; Duffy,

2014, 2016; Neumann, 2004). Such terms and approaches may be appropriate when dealing with well-organized international cartels (Wasser et al., 2018), but are not appropriate when dealing with local villagers hunting bushmeat or collecting medicinal plants for sustainence and will lead to alienation and hamper community cooperation. The alienation will be particularly acute in situations where the forest is embedded in a landscape with high human density, as people often make transgressions and enter protected areas for collecting small amounts of fuelwood, medicinal plants, and other non-timber forest products that are not available in the rest of the landscape (Naughton et al., 2011). The lure of protecting endangered species and forests from encroachment is an attractive feature but regardless of the means of deployment, the number of sensors required for it to be effective can be enormous given the structural complexity and area of forests and drones will be ineffective when trying to detect hunters below the canopy of dense growth. Researchers, managers, and funders should be acutely aware of differences between how protected areas in the savannas versus the tropics can be made safer.

Even when sensors are deployed with the aim to monitor biodiversity, the landscape of fear created by conservation surveillance can impact the communities (Humle et al., 2014; Sandbrook, 2015). The ease with which the gaze of the technology can shift from monitoring biodiversity to surveilling people reinforces the unease. People living in the communities will become involuntary objects of interest to the algorithm; being tracked every time they come near the forest or enter it for offenses that authorities in many countries are now reconsidering, such as collection of medicinal plants. Entering protected areas is typically a punishable offense. Thus, misidentification of people or activity can have severely negative life altering consequences. It will also lead to people destroying sensors and poachers are likely very good at finding sensors, like camera traps, and knowing when researchers place sensors in the forest. A researcher in Kibale turned camera trap images of sensors over to authorities, leading to an arrest, which in turn resulted in it being impossible to use camera traps in the area as they were quickly found and destroyed.

Conclusion

There have been some discussions about the responsible use of sensors in conservation. However, the conversations need to broaden to encompass those who enable, use, and are impacted by sensors and algorithms and the context in which their use is appropriate. The dialogue should include sensor deployments, data collection, access and storage, social implication of data use, and

the motivations of driving actors. The larger discourse surrounding the digital economy are also playing out in the field of conservation and includes many of the same actors but to date there is little critical discussion situating smart forests in this larger ecosystem of digital economy. It is important to keep in mind that the actors who could be involved in smart forests are presently setting the course of future interactions. This course will influence the expenditure of millions of dollars of conservation funds, the nature of people/park interactions, and the academic landscape of conservation science. Now is the time to think carefully about the paths being laid out. If conservation scientists do not play an active role in deciding the future, the path will be determined by tech corporations as is the case for various aspects of the digital economy (Benkler, 2019).

It is important to keep in mind that conservation does not simply involve the optimization to a single question (e.g., how to deter poaching or evaluate biodiversity). Rather it involves complex trade-offs and evaluation of cascading impacts that are highly context dependent. Different settings will require different technologies and approaches. Key characteristics of the setting will include the type of poacher (e.g., international cartels, local villagers), whether the area is home to a species with a high market value, the density of the population outside the protected area (e.g., the Amazon with a rural population density <2 people/km^2 versus the highlands of Uganda with 200+ people/km^2), and the nature of the habitat (forest versus savanna). Complex questions need to be asked, such as: Who will bear the cost of implementation? What is the timescale for benefits to accrue? Who will bear the cost of project continuation and infrastructure maintenance over decades? Should conservation dollars be invested in high-tech solutions or low-tech approaches that invest in local communities and hopefully builds good will? How will communities' perspective of the protected area and researchers be impacted by high-tech solutions? What are the opportunities for capacity and infrastructure building? What kind of questions will scientists want to answer?

Conservation science has a tradition of seizing unto new ideas branded as solutions to problems that threaten biodiversity (Redford et al., 2013). Grabbing onto fads is typically done without adequate testing of effectiveness or consideration of how particular field conditions would affect the outcome (Redford et al., 2013). Fads are often driven by the need of institutions or researchers to be seen as novel to secure funding. The technological solutions found in smart forest clearly offer valuable solutions to address some problems; however, their broad-scale and uncritical use in many situations may reflect fad following. With large corporations having significant stake, feel-good stories promoted through social media can amplify the fad, necessitating buy-in from more participants without providing the opportunity to evaluate context and suitability. Spectacular nature is a commercial product and digital technology is a crucial enabler of commercial interest. Real-time monitoring will expand the experiential scope which can engender more armchair support but will go hand-in-hand with surveillance for communities thus exacerbating the already disproportionate burden of conservation placed on them (Adams, 2019; Büscher, 2016).

As sensor ability and their associated technology improve, the smart forest approach runs the danger of shifting from one technology to the next in rapid succession and at great expense. In tropical forest conservation, where funding is limited; labor costs can be low and working with the local community is essential. A careful evaluation of the gains that smart forests offer relative to current conservation strategies is required before the conservation communities join the bandwagon and accept the panacea that corporations are offering. Big data tends to "focus on the future more than on the present and the past" (Lyon, 2014), it is important that conservation science does not create its own future problems by neglecting context.

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Funding

ORCID iD

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