Review and assessment of smartphone apps for forest restoration monitoring

RESTORATION ECOLOGY
The Journal of the Society for Ecological Restoration

SER SOCIETY FOR ECOLOGICAL RESTORATION

Check for updates

REVIEW ARTICLE

Review and assessment of smartphone apps for forest restoration monitoring

Daniella Schweizer[1,2], Rebecca J. Cole[3], Leland K. Werden[2,3], Gerald Quirós Cedeño[2], David Rodriguez[4], Kassandra Navarro[1], Jose Marcel Esquivel[1], Simeon Max[1], Fidel E. Chiriboga[2], Rakan A. Zahawi[5,6,7], Karen D. Holl[5], Thomas W. Crowther[2]

With increased interest in forest restoration comes an urgent need to provide accurate, scalable, and cost-effective monitoring tools. The ubiquity of smartphones has led to a surge in monitoring apps. We reviewed and assessed monitoring apps found through web searches and conversations with practitioners. We identified 42 apps that (1) automatically monitor indicators or (2) facilitate data entry. We selected the five most promising from the first category, based on their relevance, availability, stability, and user support. We compared them to traditional field techniques in a well-studied restoration project in Costa Rica. We received further feedback from 15 collaborator organizations that evaluated these in their corresponding field restoration sites. Diameter measurements correlated well with traditional tape-based measurements (R^2 = 0.86–0.89). Canopy openness and ground cover showed weaker correlations to densiometer and quadrat cover measurements (R^2 = 0.42–0.51). Apps did not improve labor efficiency but do preclude the purchase of specialized field equipment. The apps reviewed here need further development and validation to support monitoring adequately, especially in the tropics. Estimates of development and maintenance costs, as well as statistics on user uptake, are required for cost-effective development. We recommend a coordinated effort to develop dedicated restoration monitoring apps that can speed up and standardize the collection of indicators and provide evidence on restoration outcomes alongside a centralized repository of this information.

Key words: artificial intelligence, forest restoration, indicators, monitoring, remote sensing, smartphone apps, technology

Implications for Practice

- Improvement of smartphone app technology presents an opportunity to enable cost-effective monitoring as well as to better align the indicators measured and the objectives of restoration efforts.
- The broad array of new smartphone apps measure ecological indicators, but few socioeconomic indicators, and present benefits and drawbacks for monitoring restoration outcomes.
- For new technologies to be more broadly adopted by practitioners, they need to be accessible, equitable, and ideally, also consider the socioeconomic sustainability of restoration projects (i.e., local capacity building and employment).
- Developing an efficient, open-access restoration monitoring app, with the potential to standardize monitoring across the restoration community, would be timely and help provide evidence and consistency to inform restoration outcomes.

Introduction

In the last two decades, restoration of a wide range of terrestrial and aquatic ecosystems has taken center-stage in the global environmental arena. Of these, and given the potential contributions of forest regrowth to offset climate change (Griscom et al. 2017), efforts to restore forest ecosystems have been significantly scaled up. Initiatives like the Bonn Challenge (Bonn Challenge 2014) and the United Nations Decade on Ecosystem Restoration (United Nations 2020) have mobilized governments, nongovernmental organizations and private actors to pledge the restoration of over 350 million hectares of degraded land, and to “conserve, restore, and grow” at least a trillion trees by 2030 (https://www.1t.org/, accessed 28 February 2023). Not surprisingly, a recent

Author contributions: DS, RJC, LKW, TWC designed the study; TWC procured funding; FEC, SM supported app tests and selected monitoring indicators; FEC, RJC, GQC, KH, DR, JME collected field data; FEC, SM, DS gathered feedback from practitioners; DS conducted the review and led the writing; all authors revised and edited manuscript drafts.

[1]Restor, Fraumünsterstrasse 16, 8001, Zurich, Switzerland
[2]Department of Environmental Systems Science, ETH Zürich, 8001, Zurich, Switzerland
[3]Address correspondence to D. Schweizer, email daniellaschweizer@gmail.com; L. K. Werden, email leland@crowtherlab.com
[4]Asociación Ambiental Finca Cantaros, San Vito de Coto Brus, Puntarenas, Costa Rica
[5]Environmental Studies Department, University of California, Santa Cruz, CA 95064, U.S.A.
[6]Charles Darwin Research Station, Charles Darwin Foundation, Puerto Ayora, Galápagos, Ecuador
[7]School of Life Sciences, University of Hawai'i at Mānoa, Honolulu, HI 96822, U.S.A.

doi: 10.1111/rec.14136
Supporting information at:
http://onlinelibrary.wiley.com/doi/10.1111/rec.14136/suppinfo

assessment found that the number of tree planting organizations increased >250% in the past 30 years (Martin et al. 2021).

Forest restoration has been promoted as a win-win solution to mitigate climate change, counteract biodiversity loss (Barral et al. 2015; Brancalion & Holl 2020), conserve water and soil resources (Meli et al. 2017; Chazdon & Brancalion 2019; Christmann & Menor 2021; Allek et al. 2022), and improve livelihoods (Brown et al. 2011; Nielsen-Pincus & Moseley 2013). Yet rigorous and standardized monitoring to document these outcomes remains scarce and is often only carried out over the first few years of a project (Murcia et al. 2016; Coppus et al. 2019). Short-term monitoring is useful to predict restoration success within the first decade (Holl et al. 2018), but it is generally insufficient to characterize the long-term trajectories of ecosystem recovery (Brancalion et al. 2019). As such, it is unclear if positive ecological outcomes are common across forest restoration projects (Brancalion et al. 2019; Meli et al. 2022).

Scarce monitoring is partially due to restrictive funding sources, which are typically focused on short-term implementation metrics, such as the number of trees planted (Holl & Brancalion 2022), and because the costs of monitoring can be prohibitively high or regarded as unnecessary (Coppus et al. 2019). Yet, verifying implementation, generating robust evidence, and tracking progress toward stated goals are fundamental to unlock additional funding, scale up actions, certify projects, and use resources more efficiently (Cooke et al. 2018; Brancalion et al. 2019; Brudvig & Catano 2021).

Monitoring habitat recovery using remote sensing approaches represents an increasingly important alternative to ground-based measurements (de Almeida et al. 2020). For example, tracking ecosystem restoration progress (i.e., land cover change) with satellite and drones is becoming commonplace. These data sources inform recovery at large scales, and there is continuous development of high-resolution imagery products, such as the commercial Smallsats launched by Planet Labs (Frazier & Hemingway 2021; Planet Labs, Inc., San Francisco, CA, U.S.A.). Despite these advances, ground-based monitoring remains necessary to assess survival and growth of seedlings and small plants, for example, and are critical to ground truth and improve forest cover and biomass estimates generated by remote sensing data products (Ganivet & Bloomberg 2019).

Forest ecology and restoration ecology have long relied on ground-based techniques to quantify ecological recovery such as manually measuring tree survival, stem diameter (dbh), canopy cover (Lemmon 1956), and estimating understory vegetation and ground cover (e.g., the Braun-Blanquet cover-abundance scale; Wikum & Shanholtzer 1978). However, the advent and ubiquity of modern smartphones, plus the continuous update on sensors (e.g., high-resolution cameras and LiDAR) has led to the rapid increase of software applications (hereafter "apps") that can be used to estimate these indicators, and facilitate data collection and entry (Camp & Wheaton 2014; Andrachuk et al. 2019). As such, there has been a recent focus on using smartphones as an alternative to traditional field methods, albeit with different degrees of efficacy (e.g., Aitkenhead et al. 2014; Donovan et al. 2021; Howard et al. 2022).

If apps become efficient tools to monitor and manage data generated from forest restoration, they could enable cost-effective monitoring at scale and provide robust, verifiable, and standardized evidence on the outcomes of forest restoration initiatives. However, we lack side-by-side assessments of currently available apps and traditional field methods to gauge the usefulness of apps for monitoring. In this study, we systematically searched available apps that can collect and estimate a range of forest recovery indicators. Our search included an online component and collaboration with forest restoration organizations from different regions around the world to build a comprehensive list of monitoring apps. We further evaluated five open-access apps, with built-in capabilities for the automatic estimation of traditional forest monitoring indicators (canopy and ground cover and tree growth), by systematically comparing them to traditional field methods in a long-term forest restoration project in southern Costa Rica. In addition, 15 collaborator organizations with ongoing forest restoration projects tested and provided feedback on these apps.

Methods

Smartphone Apps Review

Between November 2021 and June 2022, we conducted a systematic search for apps on the Google Play and Apple app stores. We used the following forest monitoring related keywords for our search: "tree*," "forest," "soil," "diversity," "plant*," "animal," "bird," "fertility," "canopy openness," AND "monitor*." We also conducted a Google search using the same keywords as above and "smartphone" OR "cell phone" OR "mobile phone." We gathered additional information on monitoring apps from 31 collaborating restoration organizations, all members of the digital platform Restor (https://restor.eco; Table S1; Crowther et al. 2022).

This search strategy allowed us to create a database (Table S2), and gather published reviews and case studies about the use of apps in ecology, conservation, or restoration. We organized our findings around five primary monitoring categories: (1) soil; (2) plant survival, growth, and biomass; (3) vegetation structure; (4) biodiversity; and (5) management (Table S2). These categories follow the most commonly measured biophysical indicators of forest restoration progress (Dinh Le et al. 2011). All apps, except the *Biome* app (under development), were available for download at the time of our study.

Apps Field Assessment

Of the apps found, we selected five (Table 1) for field testing based on their: (1) ability to measure key indicators of forest recovery: tree height, diameter, ground, and canopy openness (Gatica-Saavedra et al. 2017); (2) accessibility to a broad range of users (i.e., open access and availability for download); (3) stability; and (4) technical support. Rigorous field testing is highly labor intensive, so we tested the top five apps based on resources available for this assessment.

Table 1. Apps evaluated in the Islas Project and by practitioners of collaborator organizations.

App	*Traditional Method*	*Growth and Biomass*	*Vegetation Structure*		*Cost (US$)*	*Platform*
			Canopy Openness	*Ground Cover*		
Arboreal Forest	Field sheet, dbh tape at 1.3-m height. Unit: cm	X			$29/month	IOS
Forest Scanner	Field sheet, dbh tape at 1.3-m height. Unit: cm	X			Free	IOS
Percentage canopy	Spherical densiometer at 1.3-m height. Unit: percent cover		X		$2/onetime payment	IOS
Canopy capture	Spherical densiometer at 1.3-m height. Unit: percent cover		X		Free	Android
Canopeo	1 × 1 m quadrat (percent green vegetation cover below 1 m estimated to the nearest 5%)			X	Free	IOS and Android

We compared the data collected by these apps against traditional field monitoring methods in a model experimental restoration project in southern Costa Rica (Islas Project; Holl et al. 2020). We collected app monitoring data at four approximately 1-ha restoration sites and two adjacent reference forest remnants. Sites are located in Tropical Premontane Forest (Holdridge et al. 1971) and apps were assessed in July–August 2022. Each restoration site consisted of three 50 × 50 m restoration treatments: uniform tree plantation planting, applied nucleation (planting patches of trees), and natural regeneration (no intervention). All restoration sites were of similar age (16–18 years) and were selected from a larger set of replicate experimental sites (see Holl et al. 2020 for details). Additionally, we monitored similar sized areas (50 × 50 m plot) to that of the experimental treatments in two nearby reference forests. In total measurements were taken in fourteen 50 × 50 m plots. Given that the objective of our study was to compare smartphone app to traditional monitoring approaches, the experimental restoration sites were selected to span a representative range of recovery outcomes based on tree cover and structure.

Each app was evaluated alongside its corresponding traditional field measurement approach (see Table 1 for details). Three technicians, with extensive prior experience in standard field measurements, and thorough training in the use of each app, collected the data. In each of the twelve 50 × 50 m restoration treatment plots and the two reference forests, we established four 10 × 2 m belt transects within which we measured all woody stems with diameters of ≥5 cm. Canopy openness and ground cover were measured at four points separated by 2.5 m along the center of each belt transect. We also quantified the amount of time needed to complete all measurements and record the data for app versus traditional field measurements in a subset (12 of 56 transects) of the belt transects that represented a wide range of recovery in vegetation structure. We used linear regression to evaluate the accuracy of app measurements compared to traditional field measurements. Statistical analyses were conducted in R version 4.0.3 (R Core Team 2013).

To further evaluate app utility, we collaborated with practitioners from 15 collaborator organizations (Table S1) who tested the five focal apps. Additional apps for estimating bird and plant species identification were opportunistically tested on the sites of some collaborator organizations based on their interests, as they required the presence of botanical and bird experts for critical evaluation. We summarize the feedback received on these apps in the discussion.

Results

We found 43 apps that support forest restoration monitoring, with some useful also in other types of ecosystems, by (1) estimating a monitoring indicator with the use of built-in analytical software or (2) assisting with field data entry (Table S2). Our search yielded apps that can automatically estimate plant growth (diameter and height), canopy openness, ground cover, individual leaf area, plant and bird species (Fig. 1). Others assist field monitoring by supporting the estimation of soil parameters, the monitoring of seedling planting and survival, and the creation of digital field data sheets. In the sections below, we focus on the results of the apps field-tested in the Islas Project in Costa Rica and by practitioners in 15 restoration organizations (Table 1).

Tree Growth and Biomass

The *Arboreal Forest* and *Forest Scanner* apps enable a practitioner to automatically estimate diameter (dbh), height, tree density, and conduct plot-based tree inventories. In addition, *Forest Scanner* uses the built-in LiDAR sensor of newer iPhones (iPhone 12 Pro and up) to acquire three-dimensional (3D) point cloud models of a tree from which diameter estimates and spatial coordinates are accurately derived using real-time instance segmentation (a computer vision task to detect the edges of objects in an image). Collaborators found the 3D plot created by *Forest Scanner* interesting and potentially useful, but the cost of LiDAR-equipped smartphones is currently too high (>US$1000) for widespread adoption. Collaborator restoration organizations also mentioned the technical capacity to compute useful analytics from the point clouds generated by these apps.

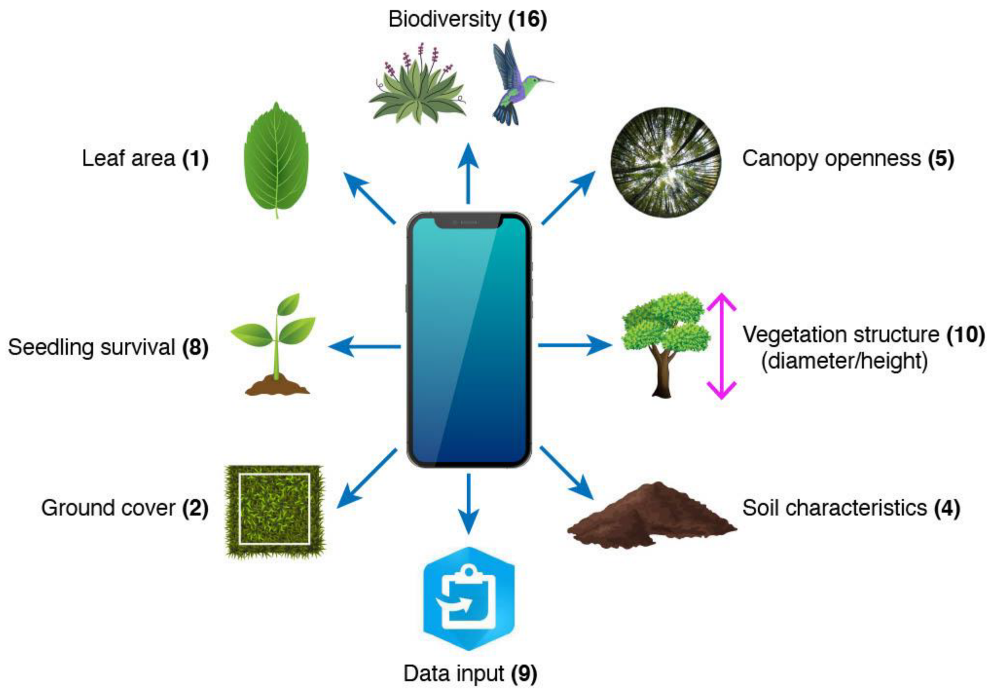

Figure 1. Forest restoration indicators monitored and functions performed by the 42 smartphone apps identified, with the number of apps that aim to address each category in parentheses. Note that some apps are able to monitor more than one indicator and thus appear in more than one category. Icons extracted from: wikimedia.org, vecteezy.com and pinterest.ch.

The ability of *Arboreal Forest* to create a digital plot or belt transect of user-selected dimensions was particularly useful in field trials. The main advantage expressed by collaborators who tested the app was not having to use a tape measure and a compass to delineate a plot, which can be time-consuming in forests with uneven terrain or dense understory vegetation. *Arboreal Forest* has a species drop-down menu, which the developer can change upon request to add region-specific tree species lists provided by the user. This was a key drawback for all collaborator organizations who tested *Arboreal Forest* in species-rich restored tropical forests, as some species would usually be missing, but the app was attractive for practitioners implementing other types of forest management practices with lower tree species numbers.

In our field evaluation, which included 179 tree stems of 15 different species, *Forest Scanner* and *Arboreal Forest* were highly correlated with tape-based dbh measurements ($R^2_{\text{forest\_scanner}} = 0.86$; $R^2_{\text{arboreal\_forest}} = 0.89$, respectively; Fig. 2A & 2B). Light conditions, epiphytes or moss on stems, and stem density affected the ability of cameras to discriminate the borders of a single tree stem. Additionally, because apps that use LiDAR require a user to walk partway around the tree to measure stem diameter, there is a potential increase in human disturbance to understory vegetation. In all field tests, *Arboreal Forest*'s height functionality was challenging to use when plots were on a slope or when vegetation obscures a direct view of the top of the tree. Not surprisingly, such issues increased data collection time and user involvement, adding more error to the computed values.

Vegetation Structure

We found five smartphone apps that estimate canopy openness and only one for ground cover (Table S2). These types of apps (Table 1) mimic the process of taking a photo and running it through specialized software to distinguish open (sky or bare ground) areas from vegetation. The canopy openness apps, *Percent Cover* and *Canopy Capture*, showed a weaker correlation to the traditional method of using a spherical densiometer ($R^2_{\text{percent\_cover}} = 0.42$; $R^2_{\text{canopy\_capture}} = 0.51$ respectively; Fig. 2C & 2D), especially in areas below 60% canopy openness. The same observation was made by our collaborator organizations in the Philippines and Ecuador. Moreover, results were extremely sensitive to light conditions and the output varied broadly depending on the contrast setting on the phone. This setting can be adjusted manually; yet a collaborator who tested the app across projects in Spain, Uganda, and Tanzania noted that this introduces subjectivity and precludes comparisons across sites.

Similarly, the percent ground cover of green vegetation measured by *Canopeo* showed a weak correlation with manual estimates done by the quadrat method ($R^2 = 0.58$). Differences to the quadrat method were larger particularly at the high end of the range when vegetation cover was above 50%, with the app frequently registering lower values in areas with densely layered vegetation cover (Fig. 2E).

Overall, the combined set of traditional field measurement methods for estimating tree diameter, canopy openness, and vegetation cover conducted in the Islas Project, including recording the data in the field, took an average of

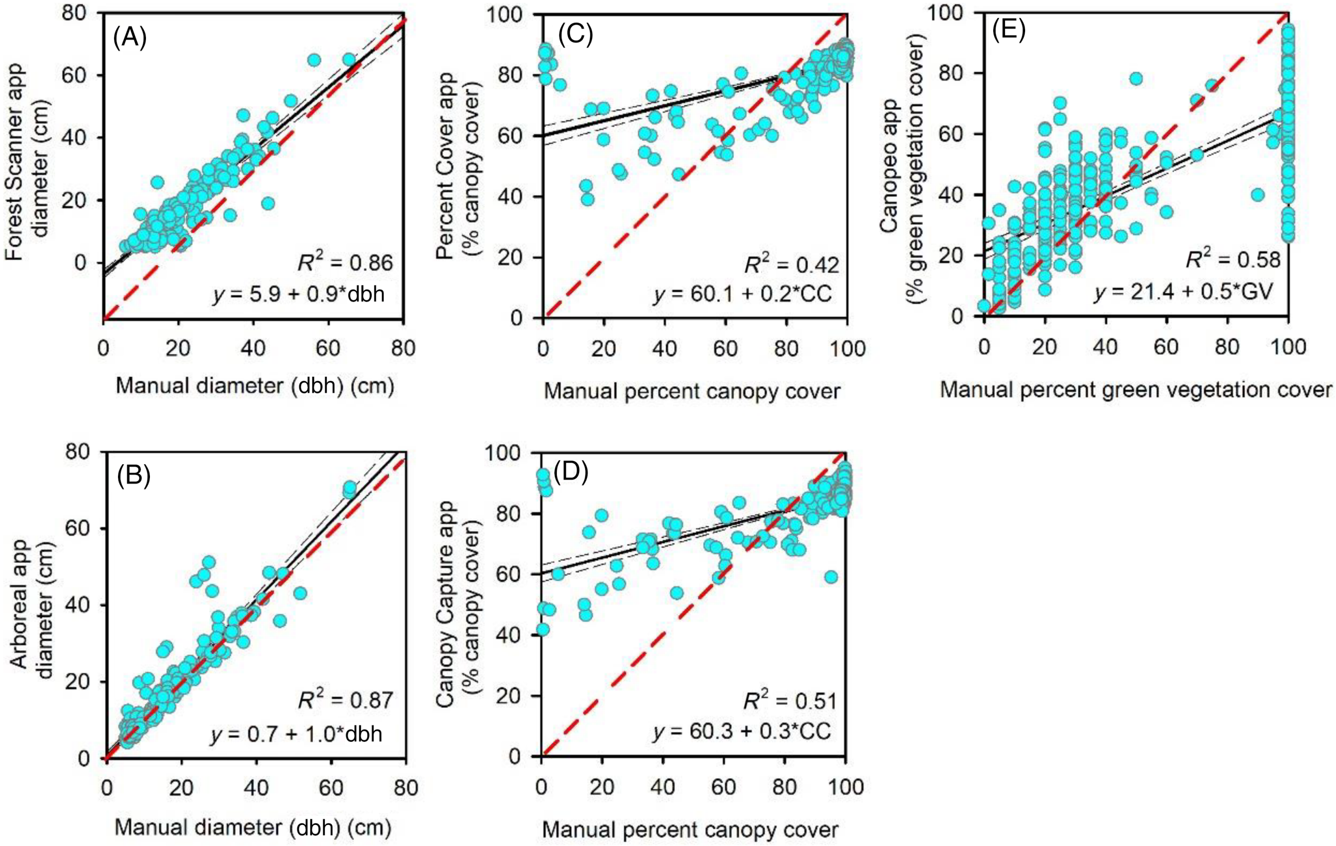

Figure 2. Relationship between the selected smartphone app measurements and traditional manual field measurements of tree stem diameter (A, B) ($n = 179$ stems), percent canopy openness (C, D) ($n = 272$), and percent green vegetation cover (E) <1.3 m above the ground ($n = 272$). The points distributed alongside the right vertical axis in panel E show where the *Canopeo* app registered highly variable values compared to the 100% vegetation cover observed using the manual method. Solid black lines show linear regression, dashed black lines represent the 95% confidence intervals, while dashed red lines show 1:1 relationship where measurements by the two instruments would be equivalent. In each case, one dot represents a single measurement.

69.7 ± 0.5% less time per belt transect than the same combined set of measurements taken using phone apps. Because not all apps store data locally, and because stored data were occasionally lost or not possible to access later due to lack of signal at the more remote field sites, it was necessary to record all app-generated data by hand in the field. As such, both, traditional and digital methods, required data transcription time.

Discussion

We found numerous apps with functionalities that estimate several key indicators of forest restoration progress. Our search did not yield an exhaustive list of apps created as part of a service (i.e., Farm trace or Veritree for carbon monitoring), or apps used internally by organizations to evaluate their work as our focus was on publicly available apps (i.e., open access apps or apps that charge a small one-time fee for download). Of those selected for the field comparison, we found that these produce estimates of certain indicators that compare relatively well with those from traditional field methods. However, further development is still required to improve their accuracy and cost-effectiveness, particularly in tropical forests.

Tree Growth and Biomass

Measuring tree growth and biomass efficiently is key to evaluating restoration progress (Viani et al. 2018), and essential if the project aims to sequester carbon and verify aboveground carbon stocks. The apps tested in the field, *Arboreal Forest* and *Forest Scanner*, provide useful features (such as the digital plot and 3D map). *Arboreal Forest* can also generate a plot-level estimate of basal area, carbon, mean canopy height, and stem density per hectare. We did not test this function in the field, however, because the built-in, automatic, estimates are based on allometric equations developed for temperate forests and not for tropical species (Arboreal, personal communication). However, the diameter and height data collected by the app can be downloaded and used to estimate biomass using appropriate allometric equations.

The key incentives mentioned by collaborator organizations for apps that automatically estimate growth and biomass were ease of use, facilitated data entry, and savings from reduced monitoring equipment purchases. However, in our field test we found measurements with the apps took approximately 70% longer on average than with traditional methods. Similarly, in an evaluation of the *Arboreal Forest* app in

Sweden, Lindberg (2020) found that it took 15% longer to take measurements with the app compared to traditional approaches. By contrast, developers of the *Forest Scanner* app reported an approximately 25% reduction of person-hours in the field. However, the assessment was carried out in low stem density forests in Japan where the model was trained (Tatsumi et al. 2022), and not in high-density tropical forest restoration sites, such as where we conducted our field test.

In our field assessment, both *Forest Scanner* and *Arboreal Forest* measurements correlated well with traditional field estimates of stem diameter when tree stems were relatively clear of other vegetation, and for trees greater than 5 cm in diameter. Thus, these apps cannot be used to assess stem diameter in young restoration plantations with small seedlings. Differences in data collection time resulted from the presence of lianas, branches, and dense understory vegetation. Collaborator organizations from the Philippines and Ecuador indicated the height estimation function of *Arboreal Forest* and *Arboreal Tree* was of limited utility in dense, tropical forest restoration plots where heights can vary greatly within a single species and the top of the tree often is not visible. However, this is also the case with traditional height measuring tools, like clinometers. As such, app efficacy in remote, high-density, structurally complex tropical forests will likely improve in cases when data can directly be downloaded for postprocessing, and as in-app models get trained to distinguish occlusions like lianas.

Phones equipped with LiDAR can provide additional monitoring outputs, like the 3D plot models generated by *Forest Scanner*. While practitioners mentioned limited scalability of this approach due to the current higher cost of hardware, costs of phones equipped with LiDAR sensors will likely decrease over time. In addition, ongoing developments, such as making apps less sensitive to changing light conditions, could make these LiDAR-based apps more useful for monitoring in the future. An example of new technology that uses machine learning and segmentation methods to estimate tree diameter is the *Biome app* (not yet publicly available) that developers claim has great speed and accuracy regardless of the shape of the tree or bark overgrowth (Earthshot labs). Similar tools will surely be developed as in-phone LiDAR prices drop.

Vegetation Structure

We found several apps for estimating canopy openness in our review. Canopy openness is a proxy for understory light environment and productivity and is an important factor for plant growth and tree species recruitment (Holl et al. 2018; Russavage et al. 2021). Prior to the advent of apps, canopy openness was measured either manually with a densiometer, or via a two-step process of taking a hemispherical photo of the canopy and extracting metrics with postprocessing software. Now, smartphones take hemispherical photos using a built-in or separately purchased clip-on fish-eye lens (approximately US$30), and the app provides image processing and results on-site, which practitioners found useful.

Despite the potential utility of these apps, canopy openness readings in our field trials were highly variable, sometimes correlating well and at other times providing very different values compared to densiometer readings, especially in areas with relatively open canopies (below 60%). As with standard hemispherical photography, the method using smartphones is prone to errors due to the pinhole effect of the camera (susceptible to light conditions), the threshold established to differentiate sky from vegetation, and the method of binary classification of open versus closed areas (Najafabadi 2014). A potential approach to selecting appropriate contrast settings under varied environmental conditions is regular side-by-side calibration of the smartphone app with a densiometer in the field, although this has yet to be thoroughly tested. In addition, we recommend taking pictures at similar times of the day and under similar weather conditions so measurements are more comparable.

Beeles et al. (2021) found that smartphone hemispherical photography characterized broad gradients of canopy openness similarly to a spherical densiometer, but typically yielded under- or overestimates of canopy openness at low and high cover values, respectively. This relationship held regardless of canopy types (deciduous, mixed, or coniferous canopies). Additionally, the authors noted that smartphones tended to generate inaccurate measurements of canopy openness across a range of environmental conditions (e.g., differences in solar irradiation, moisture, and cloud cover). Densiometers, on the other hand, require no special considerations—an observation echoed by our collaborator organizations. However, when multiple field crews are collecting data over long periods of time, smartphone apps may diminish human-caused discrepancies in overall estimates (Beeles et al. 2021). Ultimately, practitioners need to evaluate the trade-offs among complexity, accuracy, cost, and postprocessing times when deciding which tool to use for the estimation of canopy openness (Russavage et al. 2021).

Another key indicator of forest recovery following restoration is ground or understory vegetation cover. The *Canopeo* app has been designed to estimate green vegetation cover but is mainly used in agricultural settings to estimate area covered by crops versus bare ground. The discrepancies we found between the manual quadrat method and this app may be due to the high variation in vegetation color and light conditions in forest understory vegetation. Overall, we did not find this app to be particularly useful in a restoration setting, as it cannot distinguish between different shades of green and brown (such as grass vs. broad leaves or moss, or soil vs. leaf litter). This is an important limitation as reduction of grass cover is an important factor that determines restoration progress in many tropical restoration forest sites (Holl et al. 2018).

Although our collaborators found the apps tested fairly easy to use, our Islas Project field evaluation showed that user training and development of a replicable, simple methodology was required to guarantee consistent data collection. This experience was echoed in an evaluation of smartphone apps for community-based monitoring of REDD projects (Pratihast et al. 2013).

Due to time and resource limitations, we did not field-test apps that track survival and geotag tree seedlings, such as

Treemapper, *Treetrakker*, and *Veritree*. These apps, however, can increase transparency and accountability of forest restoration and tree-planting efforts, especially if they provide open-access visualizations of tree locations and status. Since estimating seedling survival is a common practice for many restoration organizations, we believe such apps will be increasingly developed and adopted in response to monitoring and reporting demands by project funders.

A Debrief on Species Identification Apps

We found several apps that support species identification, and although they were not systematically tested, collaborator organizations also provided useful feedback on their potential utility. Most apps in this category can automatically identify common plant and animal species (six apps for plants and seven for animals), while others support the identification of invasive species. Most apps for animal identification focus on birds. Species identification apps have generally been created with community science goals in mind, in an effort to reconnect users to their natural world, gather large amounts of scientifically useful taxon occurrence data (Crocker et al. 2019; Benshemesha et al. 2020; Aristeidou et al. 2021), or training machine learning for automatic visual recognition of species.

Some species identification apps are linked to a large network of plant and animal identification experts (The Global Biodiversity Information Facility; Goëau et al. 2013). This suggests continuous development is likely, and these apps may become more useful for restoration monitoring in species-rich forests in the future. Going forward, with developments in deep learning and larger training datasets, machine learning holds great potential for increasing accuracy and scale on these types of apps (Kelling 2018; Kress et al. 2018; Johnston et al. 2021). *BirdNet*, for example, uses deep machine learning to identify bird species from audio recordings (Vellinga et al. 2017). According to a recent study, this app could identify 984 bird species across North America and Europe with 79% accuracy in single-species classification (Kahl et al. 2021). In our case, an expert ornithologist tested the *BirdNet* app and correctly identified 25 different species in the Islas Project. In many cases, however, the app did not confirm a detection because of the simultaneous calls from different species, leading to low accuracy that required the ornithologist to confirm the detection. When using this apps one must be aware that (1) only more common species are generally identified correctly, and (2) when a given species is identified incorrectly several times, this error can perpetuate in the app (Altrudi 2021).

Overall, the feedback received from collaborator organizations is that these apps currently have very limited utility for identifying plant species in biodiverse forests, where local botanical expertise is still necessary. A further key drawback for use of species identification apps in remote or rural areas is that while some store data locally, most need to be online to retrieve species identifications.

Final Remarks

Some monitoring apps in our review were no longer available at the end of the project (i.e., percent cover), which hinders wider adoption by practitioners. The short lifespan of some apps is related to recurrent fees in Google Play or the App Store and the need for continuous app maintenance and development costs in the face of low user-uptake (i.e., Howard et al. 2022). Assessments of the cost to develop and maintain apps are rare (3 of 71 studies reviewed in Andrachuk et al. 2019); accordingly, we call for further estimations of the true costs of app development and maintenance, as well as for estimations of end-user uptake/utility so the community can better gauge the trade-offs involved in new app development.

Continuous improvement of sensors and machine learning applications on smartphones suggests the role of apps in monitoring will likely increase in the future. Here, we showed the wide range of indicators apps can currently estimate, and the application some emerging to monitor forest restoration. Yet, for apps to be truly effective and efficient in monitoring restoration outcomes, further improvement is needed for their use in biodiverse tropical forests.

Developing an efficient, open-access restoration monitoring app with the ability to estimate a set of common monitoring indicators including survival, growth, biomass, and vegetation structure would greatly simplify mentoring efforts for practitioners. Given current efforts to standardize restoration monitoring during the UN Decade on Ecosystem Restoration, developing a "universal" restoration monitoring app would be timely and help provide evidence-based verification of restoration outcomes to be integrated into emerging centralized repositories for this information.

Acknowledgments

The authors thank all forest restoration collaborator organizations who shared information about their monitoring protocols and their knowledge on apps. Special thanks to organizations who collaborated in field-testing the apps. The authors thank the Google.org (grant reference TF2012-096892) and the Crowther Lab for financial support to conduct this work. The Islas Project has been supported by NSF DEB grants; the most recent award is 20-116653. Open access funding provided by ETH-Bereich Forschungsanstalten.

LITERATURE CITED

Aitkenhead M, Donnelly D, Coull M, Hastings E (2014) Innovations in environmental monitoring using mobile phone technology—a review. International Journal of Interactive Mobile Technologies 8:42–50. https://doi.org/10.3991/ijim.v8i2.3645

Allek A, Viany Prieto P, Korys K, Rodrigues AF, Latawiec AE, Crouzeilles R (2022) How does forest restoration affect the recovery of soil quality? A global meta-analysis for tropical and temperate regions. Restoration Ecology 31:E13747. https://doi.org/10.1111/rec.13747

Altrudi S (2021) Connecting to nature through tech? The case of the iNaturalist app. Convergence 27:124–141. https://doi.org/10.1177/1354856520933064

Andrachuk M, Marschkea M, Hings C, Armitage D (2019) Smartphone technologies supporting community-based environmental monitoring and implementation: a systematic scoping review. Biological Conservation 237:430–442. https://doi.org/10.1016/j.biocon.2019.07.026

Aristeidou M, Herodotou C, Ballard HL, Higgins L, Johnson RF, Miller AE, Young AN, Robinson LD (2021) How do young community and citizen science volunteers support scientific research on biodiversity? The case of iNaturalist. Diversity 13:318. https://doi.org/10.3390/d13070318

Barral MP, Rey Benayas JM, Meli P, Maceira N (2015) Quantifying the impacts of ecological restoration on biodiversity and ecosystem services in agroecosystems: a global meta-analysis. Agriculture Ecosystems & Environment 202:223–231. https://doi.org/10.1016/j.agee.2015.01.009

Beeles KL, Tourville JC, Dovciak M (2021) Characterizing canopy openness across large forested landscapes using spherical densiometer and smartphone hemispherical photography. Journal of Forestry 120:37–50. https://doi.org/10.1093/jofore/fvab046

Benshemesha J, Southwellb D, Barkerd R, Mccarthy MA (2020) Citizen scientists reveal nationwide trends and drivers in the breeding activity of a threatened bird, the malleefowl (*Leipoa ocellata*). Biological Conservation 246: 108573. https://doi.org/10.1016/j.biocon.2020.108573

Bonn Challenge (2014, August 2022). URL http://www.bonnchallenge.org/content/challenge

Brancalion PHS, Holl KD (2020) Guidance for successful tree planting initiatives. Journal of Applied Ecology 57:2349–2361. https://doi.org/10.1111/1365-2664.13725

Brancalion PHS, Meli P, Tymus JRC, Lenti FEB, Benini RM, Silva APM, et al. (2019) What makes ecosystem restoration expensive? A systematic cost assessment of projects in Brazil. Biological Conservation 240:108274. https://doi.org/10.1016/j.biocon.2019.108274

Brancalion PHS, Niamir A, Broadbent E, Crouzeilles R, Barros FSM, Almeyda Zambrano AM, et al. (2019) Global restoration opportunities in tropical rainforest landscapes. Science Advances 5:1–11. https://doi.org/10.1126/sciadv.aav3223

Brown DR, Dettmann P, Rinaudo T, Tefera H, Tofu A (2011) Poverty alleviation and environmental restoration using the clean development mechanism: a case study from Humbo, Ethiopia. Environmental Management 48: 322–333. https://doi.org/10.1007/s00267-010-9590-3

Brudvig L, Catano CP (2021) Prediction and uncertainty in restoration science. Restoration Ecology. e13380. https://doi.org/10.1111/rec.13380

Camp RJ, Wheaton JM (2014) Streamlining field data collection with mobile apps. Eos, Transactions American Geophysical Union 95:453–454. https://doi.org/10.1002/2014EO490001

Chazdon R, Brancalion PHS (2019) Restoring forests as a means to many ends. Science 365:24–25. https://doi.org/10.1126/science.aax9539

Christmann T, Menor IO (2021) A synthesis and future research directions for tropical mountain ecosystem restoration. Scientific Reports 11:2394. https://doi.org/10.1038/s41598-021-03205-y

Cooke SJ, Donaldson AM, Taylor LA, Rytwins JJ (2018) Evidence-based restoration in the Anthropocene—from acting with purpose to acting for impact. Restoration Ecology 26:201–205. https://doi.org/10.1111/rec.12675

Coppus R, Romijn JE, Méndez-Toribio M, Murcia C, Thomas E, Guariguata MR, Herold M, Verchot L (2019) What is out there? A typology of land restoration projects in Latin America and the Caribbean. Environmental Research Communications 1:1–13. https://doi.org/10.1088/2515-7620/ab2102

Crocker E, Condon B, Almsaeed A, Jarret B, Nelson CD, Abbott AG, Main D, Staton M (2019) TreeSnap: a citizen science app connecting tree enthusiasts and forest scientists. Plants, People, Planet 2:47–52. https://doi.org/10.1002/ppp3.41

Crowther TW, Thomas SM, Van Den Hoogen J, Robmann N, Chavarrıa A, Cottam A, et al. (2022) Restor: transparency and connectivity for the global environmental movement. One Earth 5:476–481. https://doi.org/10.1016/j.oneear.2022.04.003

De Almeida DRA, Stark CS, Valbuena R, Broadbent EN, Silva TSF, De Resende AF, et al. (2020) A new era in forest restoration monitoring. Restoration Ecology 28:8–11. https://doi.org/10.1111/rec.13067

Dinh Le H, Smith C, Herbohn J, Harrison S (2011) More than just trees: assessing reforestation success in tropical developing countries. Journal of Rural Studies 28:1–15. https://doi.org/10.1016/j.jrurstud.2011.07.006

Donovan T, Balantic C, Katz J, Massar M, Knutson R, Duh K, Jones P, Epstein K, Lacasse-Roger J, Dias J (2021) Remote ecological monitoring with smartphones and Tasker. Journal of Fish and Wildlife Management 12:163–173. https://doi.org/10.3996/JFWM-20-071

Frazier AE, Hemingway BL (2021) A technical review of planet Smallsat data: practical considerations for processing and using PlanetScope imagery. Remote Sensing 13:3930. https://doi.org/10.3390/rs13193930

Ganivet E, Bloomberg M (2019) Towards rapid assessments of tree species diversity and structure in fragmented tropical forests: a review of perspectives offered by remotely-sensed and field-based data. Forest Ecology and Management 432:40–53. https://doi.org/10.1016/j.foreco.2018.09.003

Gatica-Saavedra P, Echeverría C, Nelson CR (2017) Ecological indicators for assessing ecological success of forest restoration: a world review. Restoration Ecology 25:850–857. https://doi.org/10.1111/rec.12586

Goëau H, Bonnet P, Barbe JA, Selmi S, Baki CV, Carré J, et al. (2013) Pl@ntNet mobile app, France.

Griscom BW, Adams J, Ellis PW, Houghton RA, Lomax G, Miteva DA, et al. (2017) Natural climate solutions. Proceedings of the National Academy of Sciences of the United States of America 114:11645–11650.

Holdridge L, Grenke W, Hatheway W, Liang T, Tosi J (1971) Forest environments in tropical life zones: a pilot study. Oxford Pergamon Press, Oxford, United Kingdom

Holl KD, Brancalion PHS (2022) Which of the plethora of tree-growing projects to support? One Earth 5:452–455. https://doi.org/10.1016/j.oneear.2022.04.001

Holl K, Reid JL, Cole RJ, Oviedo-Brenes F, Rosales JA, Zahawi RA (2020) Applied nucleation facilitates tropical forest recovery: lessons learned from a 15-year study. Journal of Applied Ecology 57:2316–2328. https://doi.org/10.1111/1365-2664.13684

Holl KD, Reid JL, Oviedo-Brenes F, Kulikowski AJ, Zahawi RA (2018) Rules of thumb for predicting tropical forest recovery. Applied Vegetation Science 21:669–677. https://doi.org/10.1111/avsc.12394

Howard L, Van Rees CB, Dahlquist Z, Luikart G, Hand BK (2022) A review of invasive species reporting apps for citizen science and opportunities for innovation. Neobiota 71:165–188. https://doi.org/10.3897/neobiota.71.79597

Johnston A, Hochachka WM, Strimas-Mackey ME, Gutierrez VR, Robinson OJ, Miller ET, et al. (2021) Analytical guidelines to increase the value of community science data: an example using eBird data to estimate species distributions. Diversity and Distributions 27:1265–1277. https://doi.org/10.1111/ddi.13271

Kahl S, Wood CM, Eibl M, Klinck H (2021) BirdNET: a deep learning solution for avian diversity monitoring. Ecological Informatics 61:101236. https://doi.org/10.1016/j.ecoinf.2021.101236

Kelling S (2018) Improving data quality in eBird, the expert reviewer network. Biodiversity Information Science and Standards 2:e25394. https://doi.org/10.3897/biss.2.25394

Kress J, Garcia-Robledo C, Soares J, Jacobs D, Wilson K, Lopez I, et al. (2018) Citizen science and climate change: mapping the range expansions of native and exotic plants with the mobile app leafsnap. Bioscience 68: 348–358. https://doi.org/10.1093/biosci/biy019

Lemmon PE (1956) A spherical densiometer for estimating forest overstory density. Forest Science 2:314–320. https://doi.org/10.1093/forestscience/2.4.314

Lindberg L (2020) Forest data acquisition with the application arboreal forest—a study about measurement precision, accuracy and efficiency. Swedish University of Agricultural Sciences, Uppsala, Sweden

Martin MP, Woodbury DJ, Doroski DA, Nagele E, Storace M, Cook-Patton SC, Pasternack R, Ashton MS (2021) People plant trees for utility more often than for biodiversity or carbon. Biological Conservation 261:109224. https://doi.org/10.1016/j.biocon.2021.109224

Meli P, Holl KD, Benayas JMR, Jones HP, Jones PC, Montoya D, et al. (2017) A global review of past land use, climate, and active vs. passive restoration effects on forest recovery. PLoS One 12:e0171368. https://doi.org/10.1371/journal.pone.0171368

Meli P, Schweizer D, Winowiecki LA, Chomba S, Aynekulu E, Guariguata MR (2022) Mapping the information landscape of the United Nations Decade on Ecosystem Restoration Strategy. Restoration Ecology 31:1–14. https://doi.org/10.1111/rec.13810

Murcia C, Guariguata MR, Andrade A, Andrade GI, Aronson J, Escobar EM, Etter A, Moreno FH, Ramirez W, Montes E (2016) Challenges and prospects for scaling-up ecological restoration to meetInternational commitments: colombia as a case study. Conservation Letters 9: 213–220.

Najafabadi MR (2014) Use of smartphone to derive the leaf area index. Wageningen University, Wageningen, The Netherlands

Nielsen-Pincus M, Moseley C (2013) The economic and employment impacts of forest and watershed restoration. Restoration Ecology 21:207–214. https://doi.org/10.1111/j.1526-100X.2012.00885.x

Pratihast AK, Herold M, Avitabile V, Bruin S, Bartholomeus H, Souza CM, et al. (2013) Mobile devices for community-based REDD+ monitoring: a case study for Central Vietnam. Sensors 13:21–38. https://doi.org/10.3390/s130100021

R Core Team (2013) R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria

Russavage E, Thiele J, Lumbsden-Pinto J, Schwager K, Green T, Dovciak M (2021) Characterizing canopy openness in open forests: spherical densiometer and canopy photography are equivalent but less sensitive than direct measurements of solar radiation. Journal of Forestry 119:130–140. https://doi.org/10.1093/jofore/fvaa052

Tatsumi S, Yamaguchi K, Furuya N (2022) ForestScanner: a mobile application for measuring and mapping trees with LiDAR-equipped iPhone and iPad. Methods in Ecology and Evolution 14:1603–1609. https://doi.org/10.1111/2041-210X.13900

United Nations (2020) United Nations Decade on Ecosystem Restoration. United Nations, New York.

Vellinga WP, Planque B, Jongsma SP (2017) www.xeno-canto.org: a decade on. Neotropical Birding 21:40–47

Viani R, Farah TE, Rodrigues RR (2018) Monitoring young tropical forest restoration sites: how much to measure? Tropical Conservation Science 11:1–9. https://doi.org/10.1177/1940082918780916

Wikum DA, Shanholtzer GF (1978) Application of the Braun-Blanquet cover-abundance scale for vegetation analysis in land development studies. Environmental Management 2:323–329. https://doi.org/10.1007/BF01866672

Supporting Information

The following information may be found in the online version of this article:

Table S1. Collaborator organizations who shared information on additional monitoring apps and references on their use.
Table S2. Results of the online search for monitoring apps.

Coordinating Editor: Jose Marcelo Torezan

Received: 30 October, 2023; First decision: 8 January, 2024; Revised: 9 February, 2024; Accepted: 26 February, 2024