Info Note

Open- and crowd-sourced MRV for agroforestry?

Preliminary results and lessons learned from a pilot study using Collect Earth to identify agroforestry on multiple land uses in Viet Nam and Colombia

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Key messages

- Forty percent of developing countries plan to use agroforestry to meet climate and development goals, yet available systems for measurement, reporting and verification (MRV) are not capable of counting trees in agroforestry systems.
- Before agroforestry can become an important response to climate change, countries need access to affordable, accessible tools to improve their ability to monitor agroforestry.
- We evaluated the effectiveness of Collect Earth, an open-source platform that allows assessment of land use using freely available high-resolution imagery, for identifying primary types of agroforestry systems in Colombia and Viet Nam.
- Preliminary results are mixed but showed promise. Collect Earth is highly effective in identifying some easily distinguished types of agroforestry systems (such as agrisilviculture, boundary planting, and home gardens) but falls short with others (including some types of shadow and silvopastoral systems).
- Refinements to our approach—including the integration of local expertise into the photo-interpretation process— could help Collect Earth become a valuable tool to ensure that agroforestry trees count toward climate goals.

Many countries have ambitions to use agroforestry to meet development and climate change goals. Forty percent of developing countries (59 of 147) propose agroforestry as a response in their Nationally Determined Contributions (NDCs), seven countries have proposed 10 agroforestry-based Nationally Appropriate Mitigation Actions (NAMAs), and 62% of 73 REDD+ countries identify agroforestry as a response to mitigate drivers of forest loss and degradation.

Agroforestry is strategic because the integration of trees on farms, ranches and landscapes in strategic spatial arrangements or temporal sequences can deliver livelihood, adaptation and mitigation outcomes. Agroforestry helps conserve soil moisture and improve soil fertility. It can offer shade, thereby buffering the damage that rising temperatures can do to both crops and livestock (Figure 1). Trees produce protein-rich fodder for animals as well as other products that can provide both additional nutrients and a source of income for farmers. Trees serve as carbon sinks, removing greenhouse gases (GHGs) from the atmosphere through both biomass and the soil around them. In short, agroforestry offers multiple benefits to transform human lives and the landscape.

Figure 1. Silvopastoral system in Colombia that combines trees, livestock and forages. Photo credit: N. Palmer (CIAT).

However, trees growing in agroforestry systems are rarely counted in MRV systems, either under the United Nations Framework Convention on Climate Change (UNFCCC) or otherwise. This absence has serious implications. If trees growing in agroforestry systems aren't counted in MRV systems, then in many ways they don't count: Only if agroforestry resources are measured, reported and verified will they gain access to the financial and other support they need to effectively contribute to a nation's response to climate change. Improved, robust, MRV is critical to scaling up agroforestry and documenting its benefits.

A major obstacle to monitoring agroforestry is the difficulty of detecting it in the landscape. Only a few types of agroforestry are visible using readily available and cost-effective remote-sensing products. As a result, countries cannot identify which lands have trees and which do not. Furthermore, agroforestry occurs on virtually all land uses but is not a land use itself, according to the Intergovernmental Panel on Climate Change (IPCC) definitions typically used in MRV systems. For example, agroforestry can be classified as forest when the system meets national definitions of forest. This can occur in shadow agroforestry systems where coffee, cocoa, and banana are grown under the shade of other tree species. Furthermore, agroforestry can be practiced on grazing lands in cases where trees are interspersed among pastures. Similar examples of agroforestry are present on the other IPCC land uses as well, such as wetlands (mixed rice-mangrove), settlements (home gardens and living fences), and croplands (maize-legume intercrops). Thus, the key is to be able to distinguish agroforestry within existing land-use categories.

If countries are to incentivize the use of agroforestry, there is a need to develop cost-effective and accessible tools to improve representation of agroforestry and help countries count trees. Here we report on an attempt to evaluate one such tool, Collect Earth.

Collect Earth

Collect Earth, part of the OpenForis suite of forestry management software, is a free tool that is used to assess trends in land use and land-use change (Bey et al. 2016). The method involves using publicly available imagery—ranging from very high-resolution (less than 1 m) to moderate resolution (30 m)—from DigitalGlobe, the Landsat archive, Google Earth, Sentinel 2 and Bing imagery. Plots are labelled and characterized in Collect Earth using visual image interpretation by individuals. Those individuals can be researchers, students or the 'crowd' at large. Collect Earth has become popular because it is relatively easy to use compared to other remote-sensing applications, it is free with both desktop and cloud-based applications, and because the information generated can easily be analysed and shared among users.

Collect Earth has emerged as a useful tool for monitoring land-use systems in a cost-effective manner. Bastin and colleagues (2017) demonstrated that Collect Earth has the potential to change the way we measure tree cover across landscapes. They estimated the extent of global forest land use and tree canopy cover in dryland biomes around the world by interpreting tree cover at over 210,000 plots. They observed 9% more forest using Collect Earth compared to estimates from previous remote-sensing methods. That is because Collect Earth enables interpreters to measure dispersed tree cover or open-canopy forests, areas where trees often are undercounted in typical mapping efforts using coarser-resolution data and machine-learning algorithms.

Although such early results are promising, the overall efficacy of Collect Earth for monitoring agroforestry is largely unknown. Issues such as the diversity of agroforestry systems, similarities between agroforestry systems and surrounding landscapes, and the age of the trees in the system may hinder the use of Collect Earth for monitoring agroforestry. The research reported here was intended to answer the following question: Can Collect Earth detect agroforestry systems matching country goals within MRV constraints?

Methods

Viet Nam and Colombia were chosen for the pilot study because they offer a diversity of agroforestry practices, which was critical to establishing the broad feasibility of the Collect Earth platform. At the same time, we wanted the results to be directly relevant to national and international conversations on agroforestry MRV. Viet Nam's government has expressed interest in integrating agroforestry into the 2020 revision of its NDC. In fact, the country already recognizes trees outside forests, with its last inventory reporting more than 352 million scattered trees. Colombia was selected because its government and private sector are developing NAMAs around two commodities, coffee and cattle, with interventions that include agroforestry systems (shade-grown coffee and silvopastoral cattle ranching). Cattle and coffee production are pervasive across Latin America, with many other countries (including Costa Rica, Nicaragua and Peru) considering or already having in place NAMAs on the same topics. Results from both countries therefore have broad implications.

The study set out to analyse the six agroforestry systems summarized by Feliciano and colleagues (2018). These systems are not species-specific but represent a broad typology of agroforestry spatiotemporal configurations. The systems are:

- **Agrisilvicultural systems** grow crops and trees in the same field.
- **Silvopastoral systems** integrate the grazing of domestic animals on land units that include forests.
- **Boundary plantings** are linear tree formations that can serve multiple functions, including live fencing, erosion prevention, or the production of timber, fuelwood, or fruits.
- **Shadow systems** grow coffee, tea, or cocoa under multipurpose shade trees.
- **Home gardens** are integrated systems around the homestead where fruit and timber trees are grown in association with herbs, annual and perennial crops, and livestock.
- **Woodlots** are cultivated trees, typically monocultures grown for timber.

The pilot studies included seven provinces in Viet Nam and eight departments in Colombia. We selected regions with sparse tree cover that support intensive agricultural land use (Figure 2). ICRAF staff members who do mapping in each country were consulted to ensure that the chosen regions included a range of the predominant types of agroforestry systems in each region.

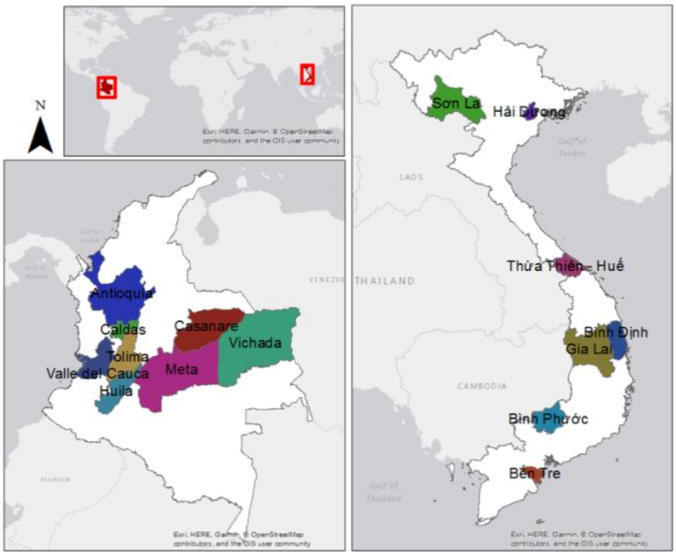

Figure 2. Overview of the selected study areas in Colombia (left) and Viet Nam (right).

A systematic random sample was created for each of the 15 study areas. We then interpreted 1,712 plots in Viet Nam covering an area of 52,275 km^2, and 3,437 plots in Colombia covering 368,170 km^2. For each plot, we used visual photo interpretation methods to assign a land-use label using the six IPCC inventory categories (cropland, forest, settlement, grassland, wetlands, and other lands), identify agroforestry systems, and estimate tree cover (both total and agroforestry-specific).

Interpretation was conducted by nine students studying geographical information systems at Kenyatta University in Kenya. The team of interpreters had a total of 24 hours—three 8-hour days—to learn the Collect Earth system and interpret all the plots. Training covered the Collect Earth software, photo interpretation methods, and classification of agroforestry systems. The students then worked together to analyse plots using available high-resolution imagery in Google Earth Pro, Google Earth Engine, and Bing Maps. Data were recorded on customized survey cards integrated into the Collect Earth platform and were saved on each interpreter's local computer. After completing the inventory, students were asked to complete surveys assessing the challenges they encountered in identifying agroforestry systems and collecting their insights as to how the identification process might be improved.

We conducted analyses in Saiku and in the R statistical software environment to summarize land use, agroforestry prevalence, and tree cover for each study site. Finally, we used published carbon stock and sequestration factors specific to each agroforestry system and region to estimate the carbon benefits of agroforestry in the study regions.

Identifying agroforestry systems

The ability to detect agroforestry using available high-resolution aerial imagery varied by agroforestry system. Interpreters consistently found that agrisilvicultural, boundary planting, and home garden systems were easy to identify from the high-resolution imagery (Figure 3). Shadow systems and silvopastoral were the most challenging to identify with high-resolution imagery, depending on the plant heights and presence of contextual indicators such as ranches. Interpreters noted the importance of being able to consult with fellow team members on difficult plots, especially in the absence of local knowledge of the region.

There was group consensus that boundary plantings were easiest to identify, as thin, linear rows of trees used as buffers along a farm or as fencing were very clear in the imagery. Home gardens were also highly visible because the presence of homes surrounded by trees and other plantings produced clear spatial patterns. Home gardens were frequently observed in Hai Duong, which aligns with information derived from interviews with provincial officials. Interpreters found that detecting agrisilvicultural systems also posed few challenges. Trees co-planted with crops, such as maize and cassava, had very clear patterns that were easy to distinguish. Interpreters did note that sometimes woodlots looked very similar to agrisilvicultural buffers.

Observations for Colombia confirmed the challenges of identifying shadow systems. Coffee is an important crop grown in the Colombian departments of Antioquia, Caldas, and Tolima. In our analysis, however, interpreters did not observe a high rate of shadow systems in these areas. This discrepancy indicates a need to determine whether the uncertainty arose from our experimental set-up or from Collect Earth itself. Due to constraints of the pilot exercise, we used interpreters in Kenya who have little experience in the tropical Americas. Persons with greater understanding of local farming systems might be better able to distinguish these systems from the available high-resolution imagery.

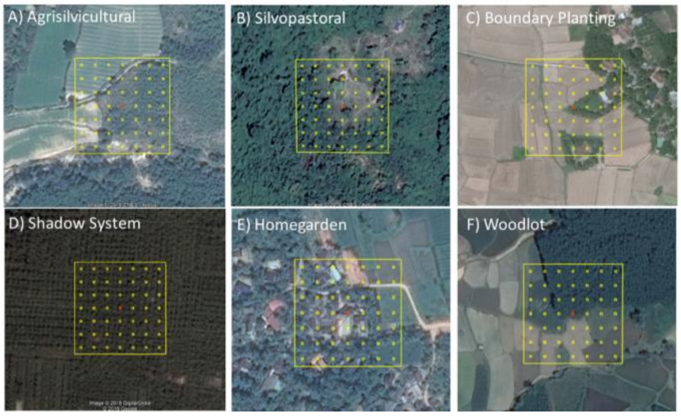

Figure 3. Example image chips for each agroforestry system.

One of the main challenges of the study was the lack of available high-resolution imagery for some parts of Colombia. Twelve percent of the inventory sample in the Colombia case study lacked adequate high-resolution imagery, with the problem being particularly acute in high-elevation regions. Where high-resolution imagery was not available, interpreters relied on the moderate-resolution data available in Google Earth Engine, such as the Landsat archive and derivatives. In the absence of high-resolution imagery, it is more challenging—though not impossible—to identify the subtler patterns produced by certain agroforestry systems, such as shadow systems. In such circumstances, one alternative is to use time-series trends of dense Landsat image stacks, which can allow interpreters to identify the distinctive planting and harvesting phenology signatures of certain crops. Indeed, a recent study successfully mapped shade-grown coffee (a shadow system) in Nicaragua using multi-seasonal Landsat 8 imagery in Google Earth Engine (Kelley et al. 2018), suggesting the potential of using Collect Earth even for difficult-to-identify systems.

Silvopastoral systems were among the most challenging to identify. The key features used to identify livestock-based systems were the presence of fodder crops and ranch buildings, but the interpreters found these features difficult to identify. Further, some extensive silvopastoral systems do not have this type of infrastructure. Some observers noted that it was challenging to distinguish silvopastoral from bare or degraded lands with interspersed trees. Training interpreters to spot additional contextual clues, such as watering holes and livestock tracks, would help them correctly identify silvopastoral landscapes.

Agroforestry systems identified were largely consistent with the IPCC land-use class expected. Agroforestry was rarely present in forests, wetlands and in the ‘other lands’ category, but it was common on croplands, and woodlots were identified on forest lands. This suggests a potential opportunity to match recognizable patterns of agroforestry systems to IPCC land uses that are already the basis of MRV systems.

Analysis of the seven provinces in Viet Nam produced results that largely agreed with information available from other sources. In the province of Ben Tre, for example, our study showed that shadow systems and woodlots were the most prevalent agroforestry systems (Figure 4). This is consistent with the reports in the ICRAF Viet Nam Spatially Characterized Agroforestry (SCA) database, which is based on provincial statistics and which indicates that cacao and coconut plantations are dominant agroforestry practices there. Similarly, our team’s identifications suggested that both agrisilvicultural and shade systems are dominant in Binh Phuoc, Gia Lai, Hai Duong, and Thua Thien Hua, findings that agreed with the SCA database.

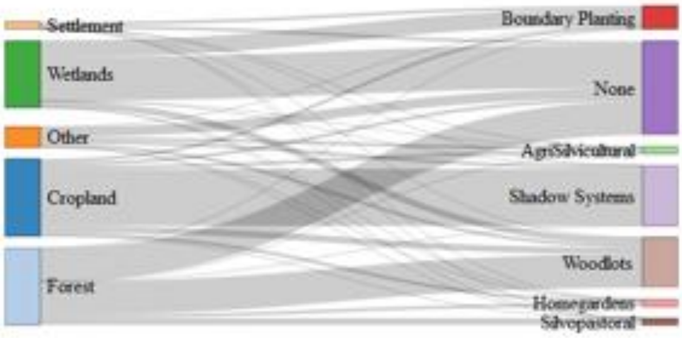

Figure 4. Land-use composition and prevalence of agroforestry systems in Ben Tre, Viet Nam. Grasslands were not observed.

Opportunities for carbon accounting

The ability of trees to sequester carbon is one of the key reasons that countries are interested in promoting agroforestry, and our study attempted to quantify these benefits. An area’s carbon budget is determined by current carbon stocks, annual sequestration, and annual emissions. Collect Earth can generate estimates of tree cover (figure 5) and areal extent of agroforestry. Data on areal extent of various systems can be combined with published carbon stock change factors to estimate carbon stocks and stock changes. For example, using the later method and estimates of carbon stock change published in two studies (Feliciano et al. 2018, Albrecht and Kandji 2003) we estimated that the annual carbon accumulation benefits range from 700,000 tC $ha^{-1}yr^{-1}$ across 232,000 hectares in Ben Tre, Viet Nam, to 4.1 million tC ha^{-1} yr^{-1} across 6.3 million hectares in Antioquia, Colombia.

Much uncertainty, however, surrounds the estimates, because of the high degree of variation of published rates. In addition, no aboveground carbon sequestration rates for boundary plantings or shadow systems were available in Asia, requiring the study to rely on published values from Latin America. These uncertainties could be reduced through more studies of local carbon accumulation rates that take into account the variety of agroforestry tree integration and management strategies. There is a need for estimates that are sensitive to specific regions, climates, and practice factors for agroforestry systems that align with the reporting categories that countries and programs already use.

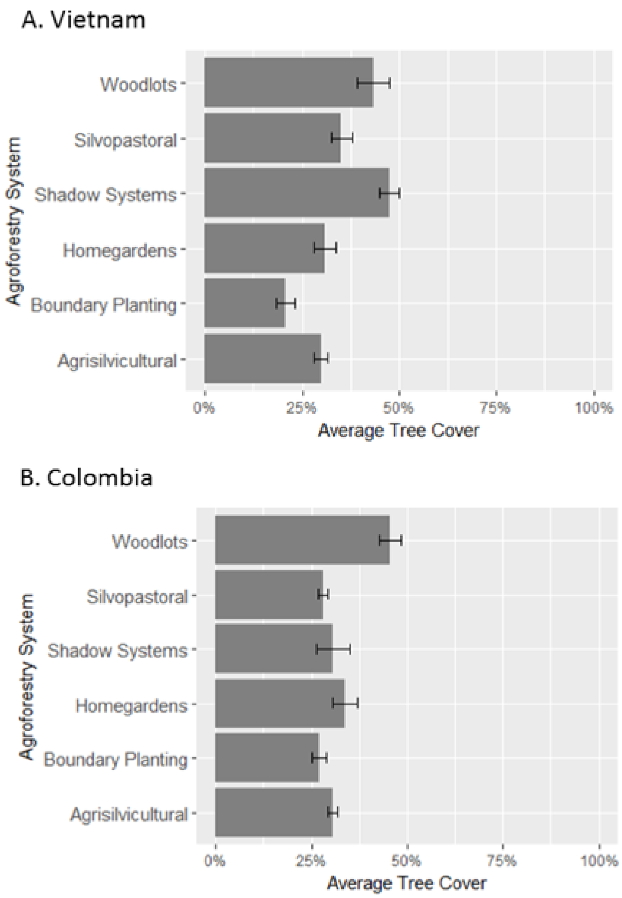

Figure 5. Percent of one-hectare plots covered by tree cover associated with an agroforestry practice in Viet Nam and Colombia. Confidence intervals represent the standard error about the mean. The standard error estimates are low since the cover estimates are recorded using increments of 10% cover.

Challenges and lessons learned

The success of the Collect Earth system depends on two broad factors: the quality of available imagery and the skill of the interpreters. One of the main challenges of working with Collect Earth was the lack of available high-resolution imagery. As discussed above, adequate high-resolution imagery was lacking for a substantial portion of the inventory sample in the Colombia case study. This challenge, however, can be overcome with additional training on how to improve accuracy through the assessment of time series.

Our pilot further suggests that identifications made by interpreters can be improved with some simple training techniques and considerations. Those conducting the training should start by providing clear descriptions of the classification systems and teaching interpreters to identify the characteristic patterns of each. Then, after each trainee labels a small subset of plots, these results should be compared to determine whether everyone labelled each plot in the same way. If inconsistencies are identified, the trainer should lead a group discussion and refer to the inventory protocols to help the trainers learn to identify the plots correctly. These quality-control checks can be repeated throughout the data collection process to improve the training and ensure consistency.

Additional information and expertise would prove useful as well. Interpreters requested access to additional information including land-use data and regional reports on crop-yields, etc. They found that this helped improve agroforestry system identification in situations where the imagery was ambiguous. Identification could be improved further by working with local experts familiar with the landscape and agricultural practices, especially for the agroforestry classes such as silvopastoral systems that have subtle signatures even in high-resolution imagery.

Crowd-based land use classification systems (e.g., GeoWiki) have been shown effective to rapidly inventory large areas. Based on our experience here, identifying agroforestry may require too much training to use the 'crowd' in this way. However, future efforts may investigate ways to achieve acceptable accuracy using crowd-based systems and Collect Earth. In the meantime, the system here is still cost-effective by comparison to alternatives.

Future efforts may do well to more rigorously assess the accuracy of estimates of the extent of agroforestry. While verifying accuracy with field work would be the gold standard, it is much more expensive and therefore tends to be cost prohibitive over the scale often desired and with the resources available. An alternative would be to give two (or more) interpreters a subset of the same sample sites to label, and then to evaluate the agreement between the two operators. Having two or more interpreters classifying the same plots would increase the trust in how the plots are being labelled and could serve as a proxy to represent accuracy (Olofsson et al. 2014).

To support efficient and cost-effective data collection, careful thought should go into the construction of the forms used to collect data in Collect Earth. The goal is to ensure all the required information is collected, while reducing the inclusion of unnecessary fields. Our pilot studies revealed improvement opportunities. In this project, we recorded only one agroforestry system at each plot. In the future we would include the ability to record multiple agroforestry systems, because in some cases more than one is present on a single plot. In most of the provinces in Viet Nam, for example, the average size of farms and landholdings was less than one hectare, making it likely that there will be multiple agroforestry practices in a one-hectare plot. Recording only the dominant system means important information is lost. In addition, we would include an attribute in which interpreters assign a coverage and tree density estimate to each observed agroforestry land use.

We also would improve the data management practices. Having multiple users collecting data on separate desktops necessitates the later merger of multiple databases. If we were to repeat this study, we would consider working with the online version of Collect Earth, which saves all entries to a project database in the cloud. This enables simultaneous data collection without the need for further database management after collection efforts have concluded. It also offers the ability to use more advanced time-series algorithms that have been customized to the signature of specific crop cycles (i.e., phenologic signals), such as those used for the study of shade-grown coffee in Nicaragua (Kelley et al. 2018). These features are not available in the desktop version.

The use of Collect Earth and tree cover estimates from remote sensing methods for precise carbon accounting is in its infancy. This is simply because the conversion from tree cover to carbon in biomass is variable. Biomass, and therefore carbon stock, is a function of both tree cover and stand structure (such as species and tree age). In addition, local conditions such as soil type, moisture regime, light and other resource availability play a role in determining tree size, so estimates of biomass from one system may not adequately represent characteristics in other conditions.

Despite these limitations, however, the advantage of the Collect Earth approach is that it offers reliable information at a relatively affordable price. This pilot, which cost less than $7,000 in total, provides a first approximation of the importance of agroforestry to national carbon budgets, and it can be used to assess relative change over time as the area dedicated to agroforestry expands or contracts. With improvements in localized carbon stock change factors, precision and accuracy could increase significantly.

Conclusions

Representation of lands – in general and in agroforestry, specifically – in land-use classification is among the most significant challenges that countries face in conducting MRV in the agriculture, forestry and land-use sector. A challenge for agroforestry is that it occurs on virtually all land uses, yet it is not itself considered a land use. Without classification schemes and measurement tools that specifically assess agroforestry, it is not possible to accurately account for the contributions it makes to a country's climate change goals. This is particularly problematic for the 40% of countries that have expressed intention in their NDCs to rely on agroforestry to help reach their goals under the UNFCCC, as well as to the numerous countries that suggest agroforestry as one solution to forest loss and degradation.

This effort piloted the use of Collect Earth to identify and represent land uses. We had mixed success, as some agroforestry systems were easy to identify by photos while others were less so. However, Collect Earth is a very cost-effective tool for MRV and could be improved through the use of experts who have local experience with tselect farming systems and through simple procedures to improve data collection. In short, the pilot's results show smoke, and with fine tuning we suspect we will find fire.

Further reading

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