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Improving uncertainty in forest carbon accounting for REDD+ mitigation efforts

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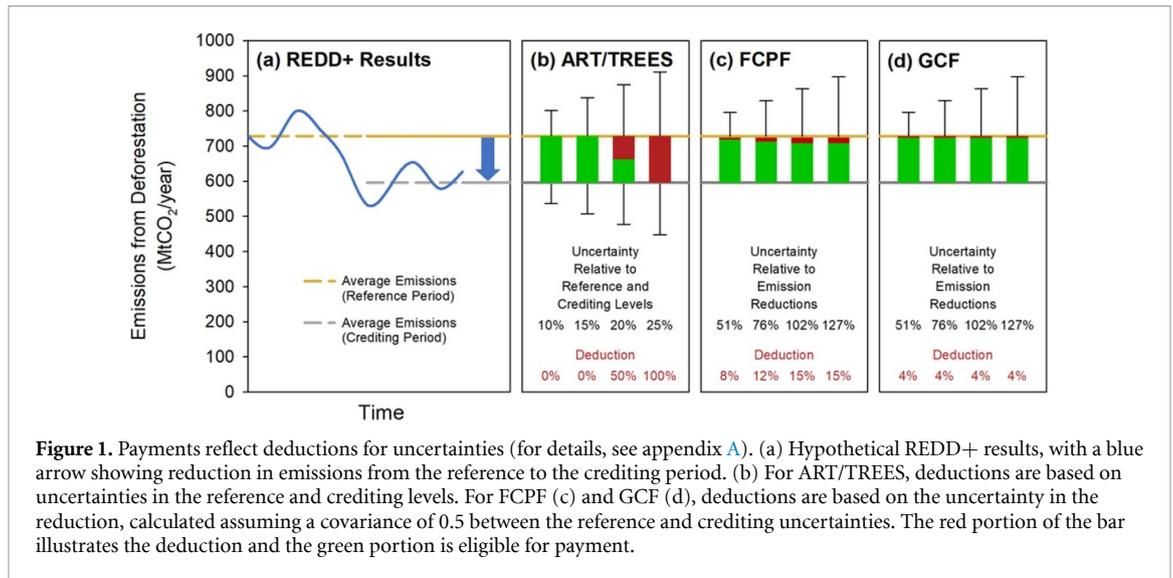
Abstract

Reductions in atmospheric concentrations of greenhouse gases are urgently needed to avoid the most catastrophic consequences of warming. Reducing deforestation and forest degradation presents a climate change mitigation opportunity critical to meeting Paris Agreement goals. One strategy for decreasing carbon emissions from forests is to provide developing countries with results-based financial incentives for reducing deforestation: nearly two billion dollars are currently committed to finance such programs, referred to as REDD+ (Reducing Emissions from Deforestation and forest Degradation, conservation, sustainable management of forests, and enhancement of forest carbon stocks). Countries participating in these programs must document the uncertainty in their estimates of emissions and emission reductions, and payments are reduced if uncertainties are high. Our examination of documentation submitted to date to the United Nations Framework Convention on Climate Change (UNFCCC) and the Forest Carbon Partnership Facility (FCPF) reveals that uncertainties are commonly underestimated, both by omitting important sources of uncertainty and by incorrectly combining uncertainties. Here, we offer recommendations for addressing common problems in estimating uncertainty in emissions and emission reductions. Better uncertainty estimates will enable countries to improve forest carbon accounting, contribute to better informed forest management, and support efforts to track global greenhouse gas emissions. It will also strengthen confidence in markets for climate mitigation efforts. Demand by companies for nature-based carbon credits is growing and if such credits are used for offsets, in exchange for fossil fuel emissions, it is essential that they represent accurately quantified emissions reductions.

1. Forest carbon credits and the importance of uncertainty

Forests are a critical part of the solution to address the global climate crisis (IPCC 2018, 2019) because of their natural ability to remove carbon dioxide from the atmosphere (Turner *et al* 2009, Lewis *et al* 2019) and the magnitude of carbon dioxide

emissions from deforestation and forest degradation (van der Werf *et al* 2009, Baccini *et al* 2012, Pearson *et al* 2017). One strategy for decreasing carbon emissions and enhancing forest carbon sinks is to provide developing countries with results-based financial incentives to reduce deforestation. Nearly two billion dollars are currently committed to such programs. Unfortunately, forest carbon



accounting is fraught with uncertainties, making it challenging to evaluate carbon mitigation efforts in the forest sector (Pan *et al* 2011). Countries participating in these incentive programs must document the uncertainty in their estimates along with their claimed emission reductions or forest sequestration relative to a baseline (Pelletier *et al* 2013, FCPF 2016; Green Climate Fund 2017, BioCarbon Fund 2020). This paper highlights common problems and presents solutions to strengthen uncertainty estimates in forest carbon accounting. Uncertainty should not be seen as a handicap; it should be embraced as an important element of tracking progress on addressing climate change.

The strategy to provide results-based payments for reducing forest carbon emissions and enhancing forest carbon sinks was agreed upon in a series of decisions under the United Nations Framework Convention on Climate Change (UNFCCC), and is referred to as REDD+ (Reducing Emissions from Deforestation and forest Degradation, conservation, sustainable management of forests, and enhancement of forest carbon stocks) (Houghton *et al* 2010). Currently, there are three multilateral programs—largely donor government funded—that offer such financial incentives to developing countries, including the Forest Carbon Partnership Facility’s (FCPF) Carbon Fund (around \$900 million committed), the BioCarbon Fund Initiative for Sustainable Forest Landscapes (ISFL, \$360 million) and the Green Climate Fund’s REDD+ Results-based Payments Pilot Programme (\$500 million). In addition, several donor governments have provided or committed results-based payments to countries on a bilateral basis (over \$2 billion for Brazil and \$1 billion for Indonesia) or through the REDD Early Movers program (which has disbursed EUR 234 million).

Countries seeking payments for forest-related mitigation efforts must establish reference levels

to use as benchmarks for assessing REDD+ performance. Currently, most countries focus on deforestation, commonly estimating emissions based on carbon stocks per unit area and the area of land changing from forest to non-forest (FAO 2019). Some countries also estimate emissions from forest degradation, and some are estimating carbon sequestration from reforestation or forest management. Forest reference levels are usually set by calculating an historical average level of emissions (Maniatis *et al* 2019) and using this as a proxy for expected future emissions. To date, 50 countries have submitted forest reference levels to the United Nations Framework Convention on Climate Change (2020).

To receive results-based payments, countries must report how they reduced emissions below their forest reference level. To avoid overcrediting, a conservative estimate would use values or assumptions that are more likely to underestimate, rather than overestimate, emission reductions (WRI & WBCSD 2005). Uncertainties in estimates of net emissions in the forest sector can be quite large, making it difficult for countries to demonstrate performance statistically distinguishable from the reference level (Grassi *et al* 2008, Köhl *et al* 2009, FAO 2017). Most results-based payment programs include procedures that reduce payments to account for uncertainty in emissions estimates (i.e. payments are made for a portion of estimated emission reductions) (Angelsen 2017; appendix A). However, to maintain incentives for countries to continue mitigation efforts while promoting honest reporting, such programs will make payments even when uncertainties are large (figure 1). In some cases, the goal of the penalties is simply to encourage efforts to reduce uncertainties.

The forest reference levels submitted to date report many uncertainties that are too low to be credible (FAO 2019). These low uncertainty estimates could be a response to the incentive system or they

could be due to confusion on how to calculate uncertainty correctly. Regardless, improving the accuracy and transparency of uncertainty estimates of forest reference levels and the reporting of results (Birigazzi *et al* 2019) is critical not only for the Paris Agreement's global stocktake, but also for the efficient use of scarce financial resources and, importantly, if these credits enter into carbon markets, to ensure that any such offset is real.

2. Common mistakes in uncertainty accounting

2.1. Omitting major sources of uncertainty

There are many sources of uncertainty in estimates of forest carbon fluxes, some more difficult to quantify than others (Houghton 2003). These uncertainty sources include sampling error (e.g. due to variability in point estimates within a land-use type), measurement error (e.g. in tree diameter, height, or wood density), model error (e.g. in regressions describing tree allometry, such as the relationship of biomass to diameter and height), and inaccurate land-use classification based on remote sensing (Hill *et al* 2013, FAO 2018). Omitting sources of uncertainty from consideration has the effect of underestimating the true combined uncertainty (Picard *et al* 2015a).

Similarly, omitting specific carbon pools, as often occurs because they are difficult to quantify, makes it difficult to evaluate the importance of these pools. There are five carbon pools in REDD+; most countries report on above- and belowground tree carbon, but few provide information on dead wood, soils, or litter (FAO 2019). Ironically, the usual justification given for omitting these sources of carbon emissions is that they are poorly known and difficult to quantify, meaning that the uncertainties may be quite large. Quantifying them would be better than ignoring them, given that all the sources contribute to the climate crisis and the shared goal is to reduce emissions for the lowest cost. Attention to uncertainty sources might reveal that efforts could be better placed by attending to these pools and sources.

2.2. Mistakes in combining uncertainties

Combining multiple sources of uncertainty to provide a single estimate, as is needed for country-level carbon accounting, can be challenging (JGM/WG1 2008, Couto *et al* 2013), in part because there are so many ways to make mistakes (Pappenberger and Beven 2006, Birdsey *et al* 2013).

One way to combine the effects of uncertain inputs is to randomly sample from their assumed distributions. In this approach, called Monte Carlo simulation (for its similarity to gambling), a carbon accounting calculation is iterated hundreds or thousands of times, with the inputs varying randomly to mimic the uncertainties in their values (Metropolis

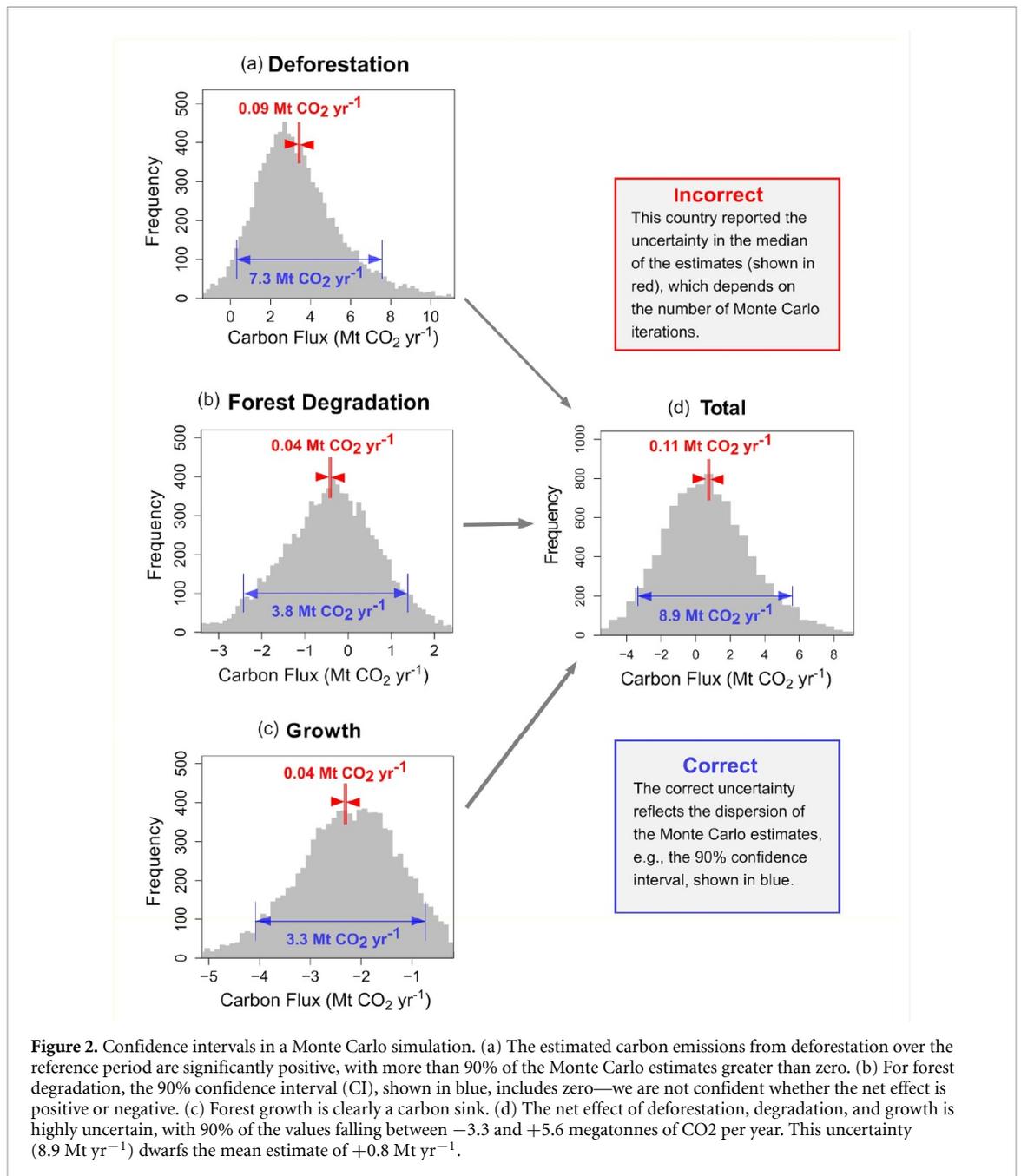
1987). The distribution of the resulting hundreds or thousands of outputs reflects the net effects of the input uncertainties.

A common mistake in interpreting this output is to report the uncertainty in the mean or median of that distribution as an indicator of the uncertainty in the output (e.g. McMurray *et al* 2017). It is not, for the simple reason that in the real world, we will not get all the Monte Carlo trials; we will only get one of them, and we do not know which one. Each trial has the same chance as all the other trials of corresponding to reality, as far as we know. This mistake is a big one, typically underreporting uncertainty by a factor of 100, because calculating uncertainty in the central tendency (e.g. the standard error of the mean) involves dividing the standard deviation by the square root of the number of 'observations,' which is commonly 10 000 trials.

An example of this mistake is shown in figure 2, which is based on a report submitted to the FCPF in 2019. The uncertainty reported to the FCPF should have been 8.9 Mt yr⁻¹, the range of the middle 90% of the distribution of Monte Carlo estimates. Instead, the uncertainty in the median of the Monte Carlo estimates was reported, which was very small (0.11 Mt yr⁻¹), because the number of estimates was very large (10 000). To accurately characterize the distribution, it is important to make a large number of estimates, but making more estimates does not diminish the uncertainty. The confidence in the best estimate (sometimes reported as the standard error of the mean, or in this case the 90% confidence interval around the median, obtained by sampling from the estimates) could be made arbitrarily small by increasing the number of Monte Carlo iterations, but the 90% confidence interval of the increased number of estimates would remain just as wide.

Using the Monte Carlo approach requires defining the distributions of the inputs; commonly, in the absence of information to the contrary, normal distributions are used, based on the standard deviation of the observations, which may not be realistic. An alternative to describing the distribution of the inputs is to resample the data. This approach requires no assumption of a distribution and is thus most true to the measured population. The drawback to this approach is that the representation of the population is only as good as the data, and if the data set is small, it may not accurately capture the range of potential values.

An analytical approach to combining uncertainty sources is easier to implement and avoids the mistake of reporting the wrong property of a distribution of Monte Carlo trials. For example, when adding uncertain estimates, the uncertainty in the sum can be calculated as the so-called 'sum in quadrature' of the uncertainty in the inputs, a formula that can be traced back to Gauss (1823). The uncertainty in a sum can be estimated by squaring the uncertainties



of the component quantities, adding them together, and taking the square root of the sum—as long as the uncertainty sources are independent (sometimes they are not; see below). This approach, referred to as Approach 1 in the IPCC guidelines (IPCC 2006), was commonly used in early submissions to the UNFCCC. Since 2013, the Monte Carlo approach (Approach 2 in IPCC parlance) has been required for participation in the FCPF. Using multiple approaches to combine uncertainties could be a good strategy for identifying some of these common mistakes.

2.2.1. Independent vs. shared sources of uncertainty in space

For both the analytical approach and the Monte Carlo approach to combining sources of uncertainty, it is

easier to treat the various sources as independent than to account for the relationships among them. Misrepresenting these relationships, either by assuming that uncertainties are independent when they are shared, or assuming that they are shared when they are independent, is another common source of mistakes in uncertainty accounting.

When combining uncertainties from multiple land areas, treating all uncertainty sources as independent can result in very low combined uncertainty. For example, in 2015, one country reported a reference level for carbon emissions with an uncertainty of only 1.5%. This calculation involved 18 forest types, with uncertainties based only on sampling error, which averaged 19% (and ranged from 2% to 92%). Combining values that range from 2 to 92

to obtain a summary of 1.5 seems counterintuitive, because we are more familiar with averaging observations than uncertainties. A weighted average of the carbon emissions would lie between the highest and lowest values. But the uncertainties in carbon emissions, if independent, do not add directly—they sum in quadrature—because any estimate could be either too high or too low, and combining opposing errors can give an answer closer to the truth. However, if the uncertainties were shared, over- and under-estimates would coincide, and they would sum normally.

Another report submitted in 2019 used a national-scale sampling error of 10%, assigned this to all the forest types, and then combined them as if they were independent. If there were two evenly distributed forest types, this would give a combined uncertainty of 7% (using analytical uncertainty propagation, the square root of the sum of squared uncertainties in this case is $\sqrt{(10\% \times 0.5)^2 + (10\% \times 0.5)^2}$); if there were 20 forest types, each 5% of the land area, the combined uncertainty would be 2.2% $\sqrt{20 \times (10\% \times 0.05)^2}$, and so on, down to vanishingly small uncertainties with very large numbers of forest types. Thus it appears to be advantageous for uncertainty reporting to consider as many forest types as possible.

However, these reports of small uncertainties, although correct for sampling error alone, fail to account for many other sources of uncertainty. Those sources that are shared are not diminished by dividing up the landscape. For example, the belowground biomass of forests is often estimated from aboveground biomass, using a ratio (root:shoot) measured at another location. Measurements of root biomass are rare, because they are costly and destructive; thus, the same root:shoot ratio is commonly used across many forest types, because the true root:shoot ratios are unknown. Similarly, although forest inventory data are collected independently across forest types, they are usually converted to carbon stores using common allometric relationships, tissue density, and carbon fraction. These sources of uncertainty, which may amount to 5%–10%, are not diminished by applying them to multiple forest types (Martin and Thomas 2011, van Breugel *et al* 2011). To the degree that they are in error, they are in error in the same direction in every instance, and for this reason it is a mistake to combine them as if they were independent (Hill *et al* 2013).

The two examples described above did not incorrectly combine uncertainties, they merely omitted sources that should have been treated as shared. Summing in quadrature is incorrect when used to combine shared uncertainties, as illustrated in a 2017 report, in which carbon emissions of 19% from the area in rainforest and 24% from the area in mesophytic forest were combined to give a country-level uncertainty of 15%. Summing in quadrature was not appropriate for the sources that were shared,

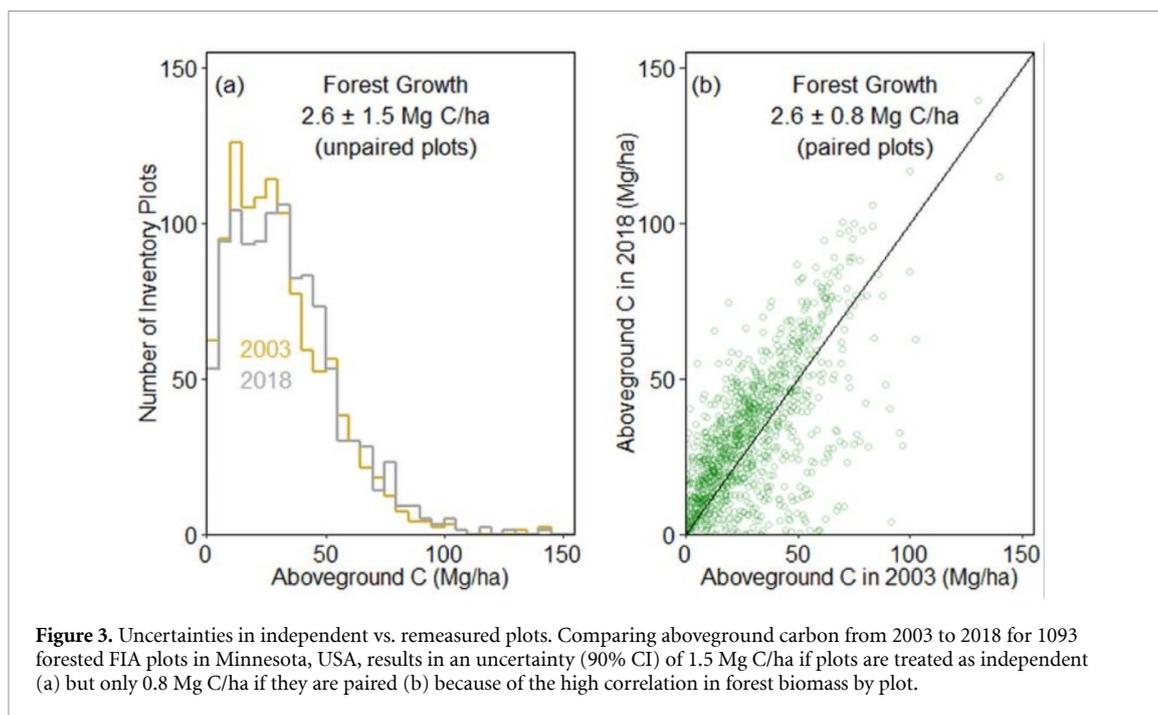
which included allometry, tissue density, and carbon fraction. Rather than using addition in quadrature, they should be combined with proper attention to correlation among the sources, which can be done analytically (JCGM/WG1 2008, Kirchner 2020). Monte Carlo sampling of shared errors, such as tree allometry, can be done correctly by assigning the same error to all trees at each Monte Carlo trial (Yanai *et al* 2010). It is easy to make the mistake of assigning error independently for each observation, which results in unrealistically small errors at large spatial scales.

2.2.2. Independent and shared sources of uncertainty in change over time

While shared sources of uncertainty in assessing carbon stocks over multiple forest types in a country give higher uncertainty than if the sources were independent, they reduce uncertainties in change over time, compared to independent sources of uncertainty. If, for example, the same root:shoot ratio is used in two successive carbon inventories, an error in that ratio will lead to similar errors in both inventories and thus to relatively small uncertainty in the net change between them. Changes over time in carbon stocks and carbon emissions are what matter to mitigating climate change (Birdsey *et al* 2013).

Similarly, revisiting the same plots over time to assess forest biomass gives a more precise estimate of change over time, by reducing the effects of plot-to-plot variability (Magnussen *et al* 2014, Mcroberts *et al* 2018a). Every plot on the landscape is different; thus, if we conducted a new sample each time, this source of variation (sampling error) would be independent at each time. The value of resampling permanent forest inventory plots is illustrated with data from the US Forest Service Forest Inventory and Analysis (FIA) Program (Bechtold and Patterson 2005) for the state of Minnesota, USA (figure 3). A pairwise comparison of estimates has about half the uncertainty (0.8 Mg C/ha) of an unpaired comparison (1.5 Mg C/ha).

Other examples of correlated error over time, besides sampling error, include allometric models. Allometric relationships are uncertain (Chave *et al* 2004, Breidenbach *et al* 2014), as are conversion factors such as wood density and root-to-shoot ratio. However, although these parameters are not perfectly known, if they are incorrect at both time periods in the same way, they do not detract as much from our confidence in change over time as if they were incorrect in different ways at the two time periods (Yanai *et al* 2012). For this reason, it is important to use the same models and methods of calculation over time (Picard *et al* 2015b). There is also uncertainty in determining the land area undergoing transitions such as deforestation or degradation, and these uncertainties are less likely to be correlated over time than the factors that contribute to estimates of carbon per unit area. When maps are used to compare rates of



change between two periods, there can be correlations in inaccuracies in classifying land cover change, which are commonly ignored (Muchoney and Strahler 2002, Pontius Jr and Lippitt 2006, Sexton *et al* 2015). Again, accounting for these correlations would reduce the combined uncertainties.

2.3. Other common mistakes

We found many other types of mistakes in uncertainty reporting. It can be challenging to handle outliers in the data, and it is tempting to ignore them if they indicate large uncertainties. One country omitted a third of their forest plots because they had trees of very large diameter, which can be common in species with buttress roots.

In some cases, country-wide averages were based on sparse local studies on the presumption that country-specific observations are better, when in fact using generalized estimates from the UNFCCC database would probably be more accurate (IPCC 2006). Local studies generally have lower variability among plots, both because they cover a smaller area, and also because research sites tend to be in pristine forests and thus are not representative of forests at the national scale. Similarly, allometric equations based on a local sample of trees will not correctly reflect the uncertainty inherent in applying them at other locations (Chave *et al* 2014).

When forest biomass is estimated by remote sensing, the uncertainty in the relationship between measurements on the ground and remotely sensed data is rarely included in the combined uncertainty estimates (Hill *et al* 2013). Using remote sensing can provide better coverage than forest inventory plots, but quantifying uncertainty in remotely sensed

biomass is challenging (Mcroberts 2010, Ståhl *et al* 2016) and may be complex and computationally difficult (Mcroberts *et al* 2019). Another important source of error seen with this approach is signal saturation. For example, leaf area calculated from optical satellite imagery underestimates rates of degradation at densities above 150 tons ha⁻¹ (Steininger 2000, Myneni *et al* 2001, Lu 2006), because highly vegetated areas look similar from space, especially in rough terrain (Sader *et al* 1989, Lu *et al* 2012). The same is true for radar imagery, which saturates between 30 and 300 tons ha⁻¹ of forest biomass, depending on the band used (Luckman *et al* 1997, Lu 2006, Woodhouse *et al* 2012). This saturation results in an underestimate of carbon change in largely intact forest that should not be ignored. The use of multiple types of sensors may enable more accurate estimates of forest density.

3. A summary of REDD+ uncertainty reporting to date

When the first reference levels were submitted to the UNFCCC in 2014, it was acceptable to submit estimates with no quantification of uncertainty (figure 4). Since then, standards of uncertainty reporting have come a long way. The FCPF's Carbon Fund requires countries to identify sources of uncertainty, quantify their contribution to overall uncertainty, and estimate the uncertainty of their reported emissions reductions. Starting in 2019, the Green Climate Fund, which uses UNFCCC submissions as a basis to determine the amount of payments to countries for REDD+ results, has required countries to provide uncertainty estimates in forest reference levels and

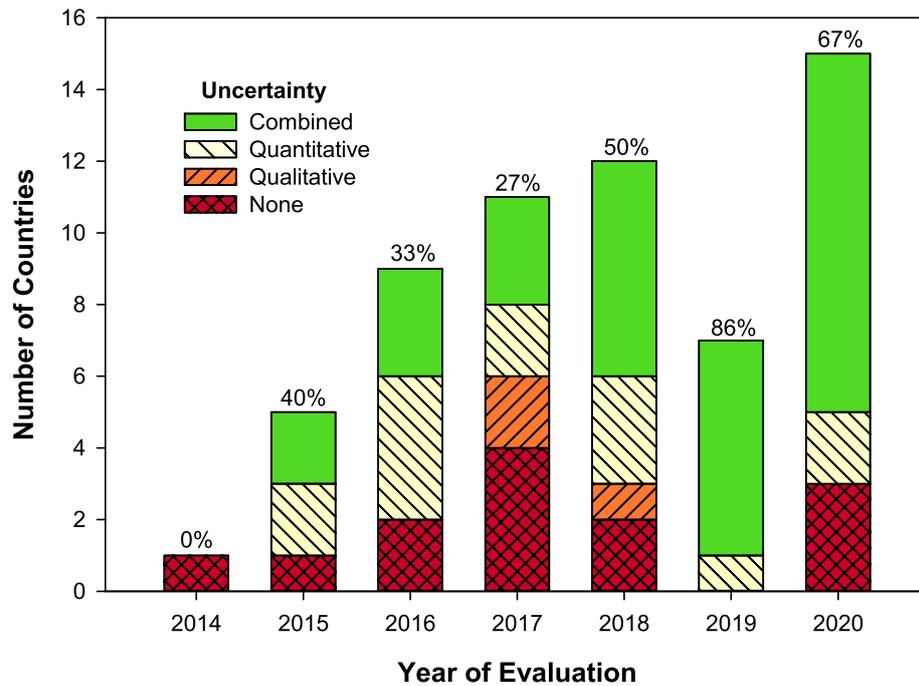


Figure 4. Improvement over time in reporting uncertainties. Number of forest reference levels submitted to the UNFCCC over time, indicating whether they gave no attention to uncertainty, some qualitative discussion but no quantification of uncertainty, some quantitative estimates of uncertainty, or a combined (if inaccurate or incomplete) accounting of uncertainty. Numbers show the percentage of submissions that included a combined uncertainty estimate. There have been 60 reference levels submitted by 50 countries, with some countries submitting more than once.

emission reductions to be eligible to receive payments (Green Climate Fund 2017). More broadly, there is a move towards greater overall transparency, with calculations of reference levels and their uncertainties made available to review panels and, sometimes, also made publicly available. This transparency makes it possible to identify mistakes in uncertainty accounting and recommend improvements.

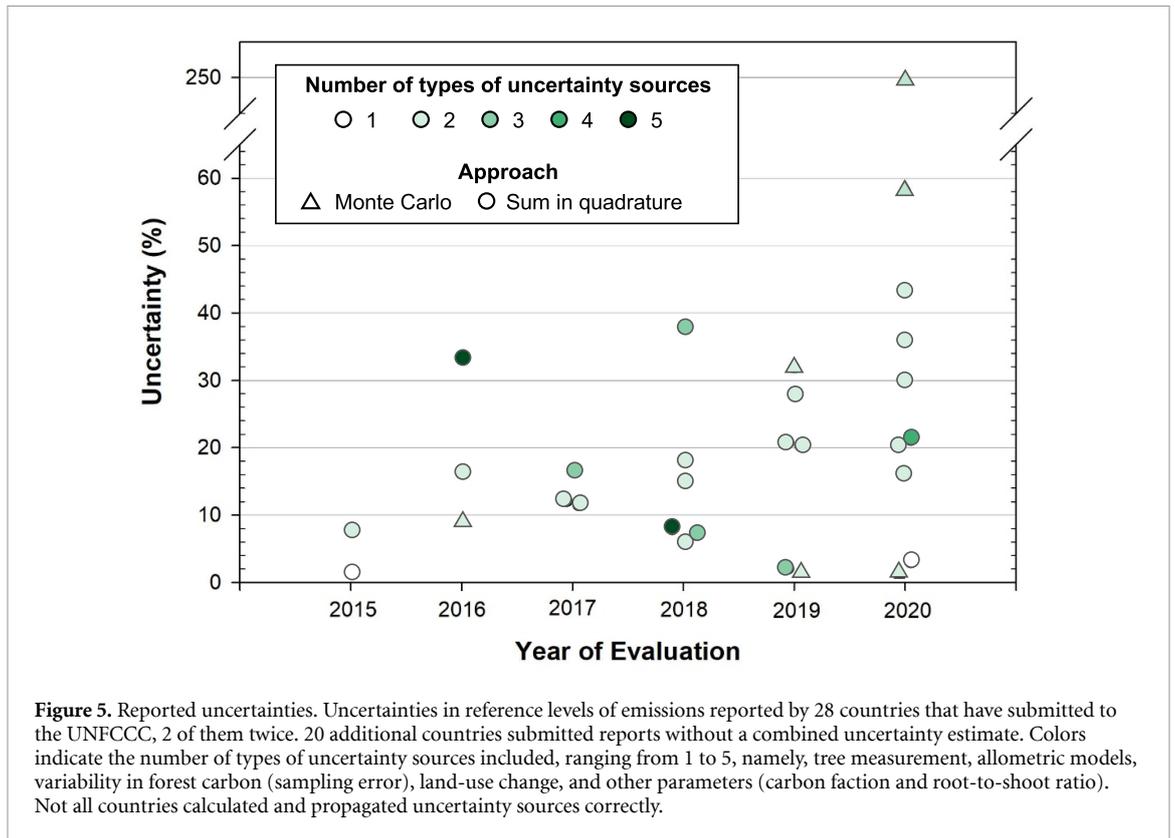
In fact, we found considerable room for improvement. As of April 2020, our examination of 60 forest reference level submissions, including resubmissions, to the UNFCCC (figure 5) and 18 Emission Reductions Program Documents to the FCPF (which contain proposed reference levels) found that very few correctly combined the uncertainty of individual components to estimate overall uncertainty. There were 19 submissions that combined uncertainties by summing in quadrature, commonly reporting a total error smaller than the individual component errors. This result would be correct if the errors of each component were independent, but often they are not, as described above. At least five countries incorrectly reported the uncertainty in the mean or median of Monte Carlo estimates, rather than the dispersion of the estimates (figure 2), resulting in reported uncertainties as low as 0.1%.

Although countries have made efforts to discuss sources of uncertainty and account for some of them, many sources are still omitted, which effectively assigns them, incorrectly, zero uncertainty. Of the

18 countries that have submitted reference levels to the FCPF Carbon Fund, none of them reported measurement uncertainty in land-use change (deforestation, degradation, afforestation), which, admittedly, is not straightforward to quantify (Mcroberts *et al* 2018b). Some countries (7) quantify at least some sources of measurement uncertainty in forest carbon density (carbon per unit area). The most widely quantified source of uncertainty is spatial sampling error, with all but 1 country reporting this for both land-use change and forest carbon density. Ten countries accounted for uncertainty in allometric models and carbon concentrations and 14 countries accounted for uncertainty in below-ground biomass estimated using root-to-shoot ratios. Finally, describing the procedures used to assure the quality of the data (QA/QC) is accepted in lieu of reporting measurement uncertainty: 14 countries took this approach for forest carbon density and 7 for land-use change. Unfortunately, meeting this requirement does not ensure that the QA/QC data are used to improve measurements; many countries collect the information necessary to quantify measurement uncertainty but have not analyzed the results.

4. Suggestions for improvement

We applaud the increasing effort devoted to uncertainty reporting, thanks in part to programs



that encourage or require uncertainties to be reported. As uncertainties are more correctly and consistently calculated, payments will be better justified in terms of performance and more fair in terms of penalties taken (figure 1).

There is still room for improvement in the reporting of uncertainty. Uncertainties are often reported without adequate discussion of the sources or recognition of bias in the estimates, and the calculations themselves are not always completely documented. Additionally, decisions are made to ignore data that would contribute high uncertainty without describing and justifying these decisions—or the justification given is that the uncertainties are high.

The benefits of repeated forest inventories, discussed above (figure 3), require accurate location of plots on the ground. Many countries have yet to establish repeatable forest inventories, and others are encountering difficulties with implementation, often arising from a lack of funding. Some countries have relied on GPS coordinates to identify plots, rather than permanently marking them, resulting in poor repeatability. Other countries have found their plot markers to be less than permanent, especially in heavily populated areas. Tradeoffs among multiple inventory objectives and increasing costs may result in decisions that increase uncertainties. For example, FAO has suggested that permanent transect plots 250 m in length would produce better estimates of biodiversity and land use (Saket *et al* 2010), but such long transects marked at only one end have resulted

in poor overlap in remeasured areas. Finally, even well marked plots can be impossible to revisit due to ecological or political conditions. Currently, few of the countries eligible for REDD+ payments have completed more than one inventory of permanent plots, but more such continuous forest monitoring systems are being developed.

Clearly, there is a need for better understanding and implementation of error quantification, especially error propagation (Chave *et al* 2004, Yanai *et al* 2010, Magnussen *et al* 2014). Guidelines should be more specific as to how to obtain uncertainties from Monte Carlo simulations; the IPCC chapter on uncertainties (IPCC 2006, section 3.2.3.2) specifies how to conduct a Monte Carlo analysis but not how to interpret the results, which has allowed the mistake documented in figure 2. The US Forest Service International Programs is currently supporting efforts to provide guidance and tools for correctly calculating and reporting uncertainties through QUERCA (Quantifying Uncertainty Estimates and Risk for Carbon Accounting). Conducting a survey of authors of REDD+ reports will identify obstacles to properly estimating uncertainty; trainings and workshops will help to build capacity, avoid mistakes in quantifying uncertainty, and enable better decision-making to improve monitoring and ultimately reduce uncertainty.

REDD+ uncertainty reporting to date has not always received adequate scrutiny. The technical review of submitted forest reference levels should be

more rigorous. The reviewers may lack knowledge of the typical levels of uncertainties that are realistic, as they have often accepted unrealistically small uncertainties without comment. The review process is more prescriptive for the FCPF Carbon Fund than for the UNFCCC; for example, the UNFCCC technical assessment provides only a list of ‘areas of improvement’ whereas the FCPF Carbon Fund can require that certain standards be met before a country can proceed in the pipeline to receive payments.

Quantifying uncertainty should be embraced, not avoided. There are many benefits of uncertainty analysis besides meeting the requirements for reporting on carbon mitigation efforts. Understanding the effect of multiple uncertainty sources on any estimate helps identify where best to direct monitoring effort towards improving confidence in those estimates. For example, an examination of uncertainty in quantifying carbon in coarse woody debris in the US FIA program revealed that estimates of wood density were the greatest source of uncertainty, and thus investments in better measurements of wood density would have the greatest payoff in terms of improved estimates of this carbon stock (Campbell *et al* 2019). In this vein, many submissions to the FCPF have identified areas for improvement, based on sensitivity analyses and an assessment of the main sources of uncertainty, and defined work plans to address them prior to the first monitoring period (FCPF 2019). Costs as well as benefits may be considered; the cost of reducing uncertainty through more intensive monitoring may exceed the benefits in carbon credit values (Köhl *et al* 2020). Smarter monitoring, such as accurate location of plots, might be achieved at lower cost than adding more plots. Fears that uncertainties would prevent payments for emission reductions (Köhl *et al* 2009) except in the case of very high deforestation (Plugge *et al* 2012) have been assuaged by programs allowing high uncertainties with small payment discounts (appendix A).

5. Conclusions

International REDD+ payment programs have spurred investment in building the capacity of countries to inventory, monitor, and report on the extent and state of their forests and changes in carbon

storage and sequestration. This investment in capacity building is paying off (Romijn *et al* 2015, Neeff and Piazza 2019). More and more countries are including uncertainty in their reference level submissions (figure 4) and using more sophisticated methods for error propagation. These improvements provide for better informed forest management as well as improved confidence in the efficacy of results-based payments.

To date, REDD+ results-based finance has largely been through donor government payments to developing countries. However, in the past two years there has been increasing interest by the private sector in purchasing ‘nature-based’ carbon offsets. If these credits are to be traded for fossil fuel emissions, they must represent real and robustly quantified carbon offsets. While there are other characteristics of forest carbon credits that must be assured—such as their permanence, avoidance of leakage, and credibility of baseline selection (Chagas *et al* 2020)—correctly quantifying the uncertainty of emission reductions is essential to safeguarding the environmental integrity of these assets. Investments now in better uncertainty quantification will allow for more targeted financing in the future to improve emission reductions and to protect the global environment.

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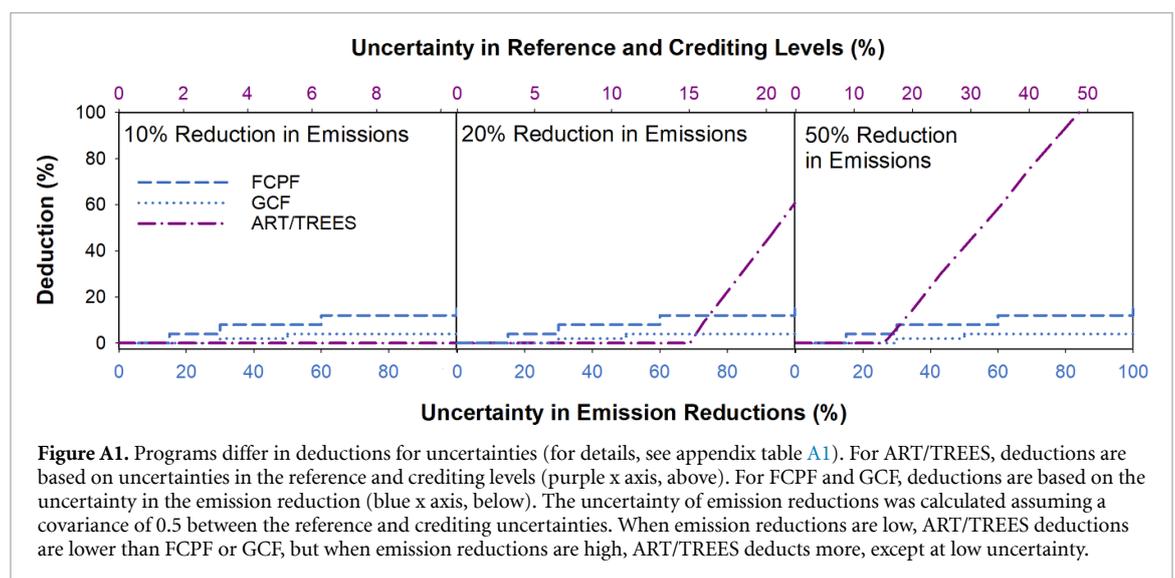
Data availability statement

No new data were created or analysed in this study.

Appendix A

Table A1. Uncertainties affect the calculation of emission reductions eligible for payment for REDD+ performance.

Program	Purpose	Uncertainty requirements and deductions
Green Climate Fund’s REDD+ Pilot Programme (Green Climate Fund 2017)	Non-market, funded by donor governments	Information on aggregate uncertainties must be reported starting in 2019. It is not clear whether ‘aggregate uncertainties’ refers to the crediting period or the claimed emission reductions. The following deductions are taken on the emission reductions that the Fund will purchase: <ul style="list-style-type: none"> • No deduction if <30% uncertainty • 2% deduction if 30%–50% uncertainty • 4% deduction if >50% uncertainty
FCPF Carbon Fund (FCPF 2016) and BioCarbon Fund ISFL (BioCarbon 2020)	Market-based pilot, funded largely by donor governments	Uncertainty of the emission reduction must be calculated using a 90% CI. Based on such calculations, the following deductions are taken on the emission reductions that the Fund will purchase: <ul style="list-style-type: none"> • No deduction if <15% uncertainty • 4% deduction if 15%–30% uncertainty • 8% deduction if 30%–60% uncertainty • 12% deduction if 60%–100% uncertainty • 15% deduction if >100% uncertainty
Verra’s Verified Carbon Standard Jurisdictional and Nested REDD+ (VCS JNR) (Verra 2019)	Market-based standard. VCS is mostly used by the private sector for voluntary offsetting; JNR has not yet been tested	Verra is currently in the process of revising the JNR standard and intends to provide more clarity on the required calculation of uncertainty. JNR currently states that: <ul style="list-style-type: none"> • Accuracy of forest versus non-forest classification shall be at least 75% • Accuracy of indirect emission calculations shall be at least 75% • Deductions to emission factors are applied if the 90% half-width CI is >10% of the estimate or if the 95% half-width CI is >15% of the estimate
The Architecture for REDD+ Transactions’ The REDD+ Environmental Excellence Standard (ART/TREES) (ART 2020)	Market-based standard, recently published; TREES has not yet been tested	Uncertainty of the emission reduction is not calculated. For both the reference and the crediting period, uncertainty is calculated using a 90% CI and: <ul style="list-style-type: none"> • If uncertainty is >15% for the reference level, it is reduced by the calculated percentage uncertainty – 15% • If uncertainty is >15% for the estimated emissions during the crediting period, such emissions are increased by the calculated percentage uncertainty – 15% • No deductions are taken if uncertainties are ≤15%



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