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Uncertain Emission Reductions from Forest Conservation: REDD in the Bale Mountains, Ethiopia

Charlene Watson[1], *Susana Mourato*[1] *and E. J. Milner-Gulland*[2]

ABSTRACT. The environmental integrity of a mechanism rewarding Reduced Emissions from Deforestation and Degradation (REDD) depends on appropriate accounting for emission reductions. Largely stemming from a lack of forest data in developing countries, emission reductions accounting contains substantial uncertainty as a result of forest carbon stock estimates, where the application of biome-averaged data over large forest areas is commonplace. Using a case study in the Bale Mountains in Ethiopia, we exemplify the implications of primary and secondary forest carbon stock estimates on predicted REDD project emission reductions and revenues. Primary data estimate area-weighted mean forest carbon stock of 195 tC/ha ± 81, and biome-averaged data reported by the Intergovernmental Panel on Climate Change underestimate forest carbon stock in the Bale Mountains by as much as 63% in moist forest and 58% in dry forest. Combining forest carbon stock estimates and uncertainty in voluntary carbon market prices demonstrates the financial impact of uncertainty: potential revenues over the 20-year project ranged between US$9 million and US$185 million. Estimated revenues will influence decisions to implement a project or not and may have profound implications for the level of benefit sharing that can be supported. Strong financial incentives exist to improve forest carbon stock estimates in tropical forests, as well as the environmental integrity of REDD projects.

Key Words: *deforestation; emission reductions accounting; Ethiopia; forest carbon stocks; REDD; uncertainty*

INTRODUCTION

Deforestation and forest degradation is driven largely by private incentives, with the benefits of ecosystem services often overlooked. A Reduced Emissions from Deforestation and Degradation (REDD) mechanism can help address this market failure by financially rewarding greenhouse gas (GHG) emission reductions from conservation, sustainable management, and forest enhancement activities (Chomitz 2007, Parker et al. 2008, Paquette et al. 2009, Mustalahti et al. 2012). A REDD mechanism under the United Nations Framework Convention on Climate Change (UNFCCC) is yet to be defined (Angelsen and McNeill 2012). Voluntary carbon markets (VCM) are the main platform through which emission reductions from forestry are currently traded (Diaz et al. 2011). The environmental integrity of REDD requires the generation of real, permanent, and verifiable emission reductions (UNDP 2009). Despite a proliferation of REDD activities, the assessment of emission reductions contains substantial uncertainty (Brown and Lugo 1992, Monni et al. 2007, Grainger 2008, Larocque et al. 2008).

In the case of avoided deforestation, emission reductions accounting requires the quantification of forest area, forest area change, and forest carbon stocks. The measurement of forest area and forest area change is being advanced through better coverage and accessibility of remote sensing imagery (Achard et al. 2004, Mayaux et al. 2005, DeFries et al. 2007, Ramankutty et al. 2007, Goetz et al. 2009, Baker et al. 2010). It is increasingly being used to infer forest carbon stocks over large spatial scales, although limitations still exist in linking imagery to on-the-ground data and in the ability to monitor forest degradation and carbon stored in deadwood and litter (Baccini et al. 2008, Baker et al. 2010, Bucki et al. 2012). Discussions are ongoing to develop and agree on methods to establish past and predicted future rates of deforestation from which the emission reductions of an intervention can be estimated (Angelsen 2008, Olander et al. 2008, Bond et al. 2009, Griscom et al. 2009, Huettner et al. 2009, Estrada 2011). In the VCM, standards set out detailed methods of good practice for establishing baselines. The Voluntary Carbon Standard is the most commonly applied, with certified projects commanding a price premium (Diaz et al. 2011, Estrada 2011). Despite advances, there remain capacity gaps in forest monitoring for REDD in countries that lack the resources and expertise to make the most in advances in satellite imagery technology or to model the drivers of deforestation (Romijn et al. 2012).

We focus on uncertainty in the estimation of forest carbon stock. Uncertainty in the carbon content of the dry biomass of a forest per unit area often results from a lack of data on key forest variables and parameters, resources, or capacity (Brown et al. 1989, Smith and Heath 2001, Andersson et al. 2009). Changes in the estimates of forest carbon stock in the FAO Forest Resource Assessment, a widely used database of global and national forest statistics, have been attributed to information availability rather than forest carbon stock change (Houghton 2005, Grainger 2008). The lack of forest monitoring data is particularly acute for Africa (FPAN 2010, Romijn et al. 2012). Reported estimates of forest carbon stocks for Africa are highly variable, from 0 to 454 tC/ha (IPCC 2006, Gibbs et al. 2007, Baccini et al. 2008). Lewis et al. (2009)

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estimated forest carbon stocks from permanent plots across Africa with an average of 202 tC/ha. While methods of generating forest carbon stock estimates are well accepted and tested by forest scientists, such local measurements or permanent sample plots are resource intensive and thus hard to conduct across large spatial scales (Nagendra and Ostrom 2011). As REDD grows in popularity, however, project developers and policy-makers have greater need for large-scale forest information.

The application of biome-averaged data for forest carbon stocks has become commonplace in emission reductions accounting from avoided deforestation (Brown and Gaston 1995, Gibbs et al. 2007, Djomo et al. 2010). The Intergovernmental Panel on Climate Change (IPCC) guidance for GHG inventories has three method tiers intended to promote broad engagement irrespective of a country's data and capacity (IPCC 2003, 2006, Baker et al. 2010). Tier 3 uses advanced estimation approaches with complex models and highly disaggregated data. Tier 2 uses country-specific forest carbon stock information with activity data at small scales. Tier 1 is based on biome-averaged and default values for forest carbon stocks and contains the greatest level of uncertainty (Böttcher et al. 2009). While IPCC guidance was not designed to produce emission estimates for REDD projects, it is the basis of many REDD standards, and the UNFCCC supports the use of IPCC guidance in REDD development (UNFCCC 2009). While data used in Tier 1 are able to capture broad ecological factors influencing forest carbon stocks, such as temperature and rainfall (Chave et al. 2004, GOFC-GOLD 2008), forest heterogeneity is obscured (Bradford et al. 2010, Houghton et al. 2001). The discrepancies in forest carbon stock methods are further compounded by the need to combine forest carbon stocks with other forest variables in emission reductions accounting (Waggoner 2009, Ciais et al. 2011).

Literature is emerging on the uncertainty in forest carbon stocks and resultant implications (Houghton and et al. 2001, Houghton 2005, Mollicone et al. 2007, Ramankutty et al. 2007, Pelletier et al. 2010). A comparison across six countries by an international panel on Global Observation of Forest and Land Cover Dynamics (GOFC-GOLD 2008) indicated that biome-averaged data overestimated forest carbon stock by 33% in Mexican temperate forest and underestimated it by 44% in African rain forest when compared to primary forest data. Saatchi et al. (2011) produced a global map of forest carbon stocks based on satellite imagery and on-the-ground forest plots. Propagating errors through the estimation process, they found uncertainty in forest carbon stocks of 38% over Latin America, Sub-Saharan Africa, and Southeast Asia. By translating errors in estimating forest carbon stocks into the environmental integrity of emission reductions in Costa Rica, Kerr et al. (2004) found uncertainty is impacted by forest type, with highest uncertainty in tropical wet forest. Pelletier et al. (2010) used five carbon stock estimates for Panamanian forests in land conversion and transition models, and found 144% difference in emission reductions between the highest and lowest forest carbon stock estimate.

A discrepancy in emission reductions as a result of forest carbon stock methods could mean the difference between a decision to implement a REDD project or not, as revenues available to alter incentives for forest conservation are dependent on the market value of the emission reductions and the costs of getting them to market. REDD project feasibility studies will often combine emission reductions estimates with VCM variables such as price, implementation, and transaction costs, further compounding the uncertainty. No standardized method of assessing or communicating uncertainty in emission reductions accounting exists, and being conservative remains a dominant approach (Mollicone et al. 2007, Grassi et al. 2008). By omitting carbon pools or taking lower bounds, the principle of conservativeness ensures a low probability that carbon emission reductions are overestimated (GOFC-GOLD 2008). By assuming zero uncertainty, conservativeness can leave decision-makers without a confidence interval of the emission reductions estimate (Andersson et al. 2009). With biome-averaged forest carbon stocks often applied in REDD feasibility studies and more complex accounting methods applied during project development, conservativeness may result in missed climate change mitigation opportunities if emission reductions are more substantial than a feasibility assessment indicates (Shoch et al. 2011). Discrepancies in emission reductions between feasibility study and project development can also erode the credibility of a REDD project, questioning its environmental integrity. Unrealistic expectations can be ameliorated if uncertainty can be quantified, reduced where possible, and communicated more appropriately (Waggoner 2009, Baker et al. 2010).

We demonstrate the financial significance of forest carbon stock methods using a proposed REDD project in the Bale Mountains of Ethiopia. Aiming to highlight the implications of the uncertainty in forest carbon stocks, we explore the emission reductions and potential REDD revenues and profits under three forest carbon stock estimates and two carbon market prices. The implications for project implementation at the case study site are then addressed. We add to current knowledge through the estimation of forest carbon stock in the Bale Mountains. We build on a limited literature on the environmental integrity of REDD and the financial implications of forest carbon stock methods, and make recommendations for improving forest data, with an overarching aim to aid REDD policy decisions.

METHODS

Study area

In the Oromia state of southeast Ethiopia, the Bale Mountains lie between 50º22'–80º08'N and 38º41'–40º44'E. Average annual temperature is 17.5ºC, and ranges from 10ºC to 25ºC, with average annual rainfall of 875 mm experienced in one long season between June and October, and one short season between March and May (Yimer et al. 2006). Moist tropical forest occurs between 2600 m above sea level (masl) and 1500 masl, and is characterized by *Hagenia abyssinica* and wild coffee (*Coffea arabica*). North of the plateau, habitats are comprised of dry forest, woodlands, grasslands, and wetlands, largely between 2500 masl and 3500 masl. Dry forests contain high-value commercial species such as *Juniperus procera* and *Podocarpus falcatus* as well as *Prunus africanus*, a threatened species. The lower altitude land of the southeast of the Bale Mountains, below 1500 masl, is dominated by acacia woodland (UNIQUE 2008, Teshome et al. 2011). The large topographical variation in the Bale Mountains is observed across wider Ethiopia, and the forest is representative of other east African montane habitats that extend through Tanzania, Kenya, and Uganda (FPAN 2010).

Rural communities in the Bale Mountains deforest to procure land for crops and livestock grazing and to meet timber and firewood needs (BERSMP 2006, BMNP 2007). This pattern is replicated over Ethiopia, with large-scale conversion of land to agriculture also playing a role at the national level (Forest Carbon Partnership Facility 2011). Between 1986 and 2009, annual deforestation in the Bale Mountains ranged from 1% to 8%, with an average rate of 3.7% (Dupuy 2009), almost four times the 1% country-wide forest loss (FAO 2010). In order to address forest decline in the Bale Mountains, a REDD project is being developed by the Oromia Regional State Forest and Wildlife Enterprise, which is supported by the Bale Eco-Region Sustainable Management Program (BERSMP), a joint nongovernmental organization program between FARM-Africa and SOS Sahel Ethiopia. The REDD project area covers 923,593 ha, including 576,856 ha of tropical dry and moist forest. To achieve a reduction in deforestation to 1% in project Year 20, participatory forest management (PFM) is being implemented across the Bale Mountains, which includes the establishment of community-based organizations, development of forest management plans, and implementation of sustainable forest management practices. PFM is regarded as a tool for REDD implementation alongside additional support for sustainable agricultural intensification, woodlot establishment, and improved fire management.

Estimating forest carbon stocks and emission reductions

Three sources of forest carbon stock information were used to model emission reductions in the Bale Mountains:

1. Ecological zone-specific forest carbon stock from the IPCC Land Use, Land-Use Change and Forestry Good Practice Guidance (IPCC 2003)
2. Africa-specific forest carbon stock from the IPCC Agriculture, Forestry and Other Land Use guidelines (IPCC 2006)
3. An estimate of forest carbon stock based on field sampling in the Bale Mountains

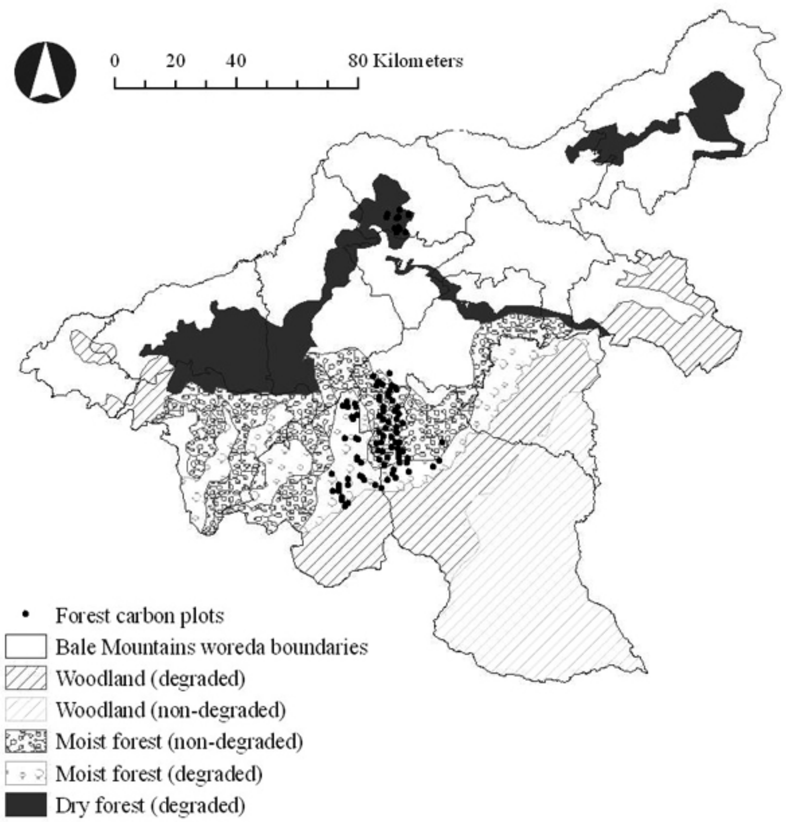
Forest plots

Primary data collection focused on the above-ground tree carbon pool of 108 forest plots of 20 m x 20 m sampled between December 2008 and April 2010 (Fig. 1). Because this carbon pool contains the greatest fraction of total living biomass in a forest, it is most immediately impacted by deforestation and degradation (Brown 1997, FAO 2003). Plots were undertaken in tropical moist degraded forest, tropical moist nondegraded forest, and tropical dry degraded forest; no nondegraded tropical dry forest remains. Stratification of the forest area was undertaken by forestry consultants using satellite imagery and expert consultation (UNIQUE 2008). Stratification helps capture forest carbon stock clusters based on variation in factors such as elevation, temperature, precipitation, and soil fertility (Houghton 2005). While uncertainty due to errors in stratification is not dealt with in this study, it is recognized that higher resolution satellite imagery or post-stratification based on factors that affect carbon stock could reduce uncertainty in forest carbon stock estimates. Plot coordinates were selected using random number generation to identify numbered map crosshairs but were limited to logistically accessible areas for which field sampling permissions had been granted. Drawing on existing forest inventory protocol (MacDicken 1997, Pearson et al. 2005, Greenhalgh et al. 2006), the diameter at breast height (dbh) was recorded for all trees within each forest plot, with a lower limit of 5 cm dbh used to define a “tree.” Canopy cover and plot slope were also recorded. Retrospective power analysis was undertaken to illustrate the minimum number of forest plots required for the mean forest carbon stock estimate to be within an error bound of 20% of the mean with 95% probability. Logistical issues prohibited a priori calculation of the sample size; however, retrospective power analysis allowed comparison of the desired number of plots to the actual number of plots sampled for a given predictive power (Pearson et al. 2005).

Biomass regression equations

To determine forest carbon stock, the above-ground biomass was first estimated per tree by applying pan-tropical mixed species broadleaf allometric regression equations that statistically relate forest attributes to above-ground biomass (Brown 1997, Eq 3.2.1 and 3.2.4). While 95% of the variation in the above-ground biomass of trees can be explained by dbh (Brown 2002), studies indicate that using measurements of tree height and wood density—the dry weight per unit volume of wood—in allometric equations can improve biomass estimates (Brown et al. 1989, Chave et al. 2005, van Breugel et al. 2011, Marshall et al. 2012). However, it is also noted that for trees with large dbh, mechanical or physiological limits can alter the relationship between height and dbh (Chave et

Fig. 1. Forest cover map of the Bale Mountains showing the location of forest plots used to estimate mean carbon stocks and forest type.



al. 2005). Few site and species-specific allometric equations exist for Sub-Saharan Africa, however, and only 15% of 850 Sub-Saharan African allometric equations use height (Henry et al. 2011, Shackleton and Scholes 2011). Ethiopian allometric equations are often single species, and equations are found to be of varying quality (Henry et al. 2011). Pan-tropical allometric equations were applied because no mixed species allometric equations exist for the Bale Mountains, and destructive sampling to generate equations was not feasible. The allometric equation was based on dbh and not height or wood density in light of the lack of data at the case study site and the difficulties in measuring tree height accurately in tropical forests. Chave et al. (2005) found that tree allometry is conserved across the tropics of Latin America, Southeast Asia, and Oceania, although insufficient data were available to assess if this was the case for the African continent. However, allometry is conserved only where applied to trees within the maximum and minimum tree dbh used to generate the equation. Trees with diameters that exceeded the upper limit of the range used to create the regression equations were therefore assumed to fall at the maximum dbh of the equation (148 cm). Although a necessary assumption, this is likely to underestimate the carbon stock in the reference period and the emission reductions if large trees are conserved in the assessment period. If in the assessment period, instead, such trees were selectively removed, emission reductions could be overestimated.

Forest carbon stocks

Tree biomass was converted using a carbon fraction of 0.47 (IPCC 2006). Plot areas were adjusted for their average slope angle using cos (slope), and carbon stock per hectare was established. The slope correction improves the likelihood that each forest plot contained the same total area as seen on a satellite image. The area-weighted means of forest carbon stocks were calculated parametrically and compared to an empirical bootstrap distribution that re-sampled with replacement 1000 times (Efron 1979, Guan 2003).

In addition to natural variation, the forest carbon stock estimate contains uncertainty from sampling error, measurement error, and the errors inherent in underlying equations and assumptions. Table 1 identifies these sources of uncertainty and the methods applied in this study to reduce uncertainty, emphasizing our focus on sampling error.

Table 1. Inputs and sources of uncertainty in estimates of forest carbon stock, as well as methods applied to reduce these uncertainties.

Input	Source of uncertainty	Method to reduce uncertainty
Selection of forest plots	Sampling error	Forest plot geo-coordinates were selected using random number generation, within logistical constraints, and good practice for sampling design and forestry inventory was followed (MacDicken 1997, Pearson et al. 2005, Greenhalgh et al. 2006, Grassi et al. 2008).
Measurement of diameter at breast height (dbh)	Measurement error	Training and education in measurement of dbh was conducted to reduce measurement error. It was ensured that trees were not measured twice or dead trees counted as living. Measurement uncertainty on a single tree of diameter 10 cm or greater has been estimated at 16% but found to average out at forest stand level (Chave et al. 2004).
Application of allometric equation	Estimation error: allometric equations originating from Asian and Latin American data	Pan-tropical equations are based on a large number of trees from Asia and Latin America spanning a range of diameters. Because destructive sampling of trees to create an area-specific allometric regression equation was not possible, the application of pan-tropical allometric equations was appropriate within dbh values used to create the regression equations. Error attributable to the allometric equation is estimated at 10–20% (Clark and Clark 2000, Keller et al. 2001, Ketterings et al. 2001, Chave et al. 2004).
Application biomass to carbon ratio	Estimation error: the carbon density of biomass components and tree species differ	The IPCC 2006 present a default value of 0.47 for tropical and subtropical forest but within an interval estimate of 0.44–0.49. This is an improvement on 0.5 suggested by Westlake (1966), but suggests a relative error of 5%.

Emission reductions

Emission reductions are evaluated by the difference between a business-as-usual (BAU) deforestation scenario and a REDD project scenario. Analysis of LANDSAT TM images from 1986, 2000, 2006, and 2009 by the BERSMP established a deforestation rate of 4%. This estimate was based on differing sensed spectral reflectance that are classified into vegetation types and then ground-truthed (Achard et al. 2001, Andersson et al. 2009). The BAU deforestation scenario in the Bale Mountains was therefore assumed to be a basic linear deforestation rate of 4% of the 2009 forest area in all forest types, as also modeled in the Bale Mountains REDD feasibility studies (UNIQUE 2008, 2010). Future project development would require the acquisition of a broader time scale of satellite imagery in addition to more complex models of forest changes, for example linked with models of the forest transition or to the drivers of deforestation (e.g., Barbier et al. 2010, Estrada and Joseph 2012).

Avoided deforestation under a REDD project is based on project goals, with the effect of PFM on deforestation being subjective rather than based on past experience. While there are findings that community forest management and greater rule-making autonomy at the local level can lead to emissions reductions and greater carbon storage (Chhatre and Agrawal 2009, Skutsch and Ba 2010), this is not universally the case. Experience of the Integrated Forest Management Project of Adaba-Dodola documented by Kubasa and Tadesse (2002) and Tesfaye et al. (2011), also located in the Bale Mountains, for example, suggests that deforestation is occurring more rapidly immediately outside of the PFM area; thus, leakage is being experienced. The estimate of reductions in deforestation, therefore, will need to be revised regularly as the intervention progresses and new information is acquired.

The annual emission reductions generated by the Bale Mountains REDD project is expressed in Eq. 1. $E_{t,i}$ are emission reductions in tons of carbon dioxide (tCO_2) in year t, utilizing forest carbon stock estimate C_i (tC/ha) where i can take the value of 1, 2, or 3, representing the three forest carbon stock estimates used to model emission reductions. D_{BAU} is the annual BAU deforestation in hectares in a without-project scenario ; D_{REDD} is the area of deforestation (ha) during the project in year t; and 44/12 is the ratio of the molecular weight of carbon dioxide to that of carbon.

$$\mathrm{ER}_{t,i} = \mathrm{C}_i(\mathrm{D}_{\mathrm{BAU}} - \mathrm{D}_{\mathrm{REDD}t})\frac{44}{12} \tag{1}$$

The annual area of deforestation under a REDD project scenario, D_{REDD}, is based on reducing deforestation below the annual BAU scenario of 4% in three stages. In years 1 to 5, D_{REDD} is 3%, in years 6 to 10, D_{REDD} is 2%, and in years 11 to 20, D_{REDD} is 1%. The total emission reductions generated by the project, $E_{project,\,i}$ (tCO_2), can be represented by Eq. 2, which sums annual emissions over the 20-year project lifespan.

$$\mathrm{ER}_{\mathrm{project},i} = \mathrm{C}_i\left(20\ \mathrm{D}_{\mathrm{BAU}} - \sum_{t=1}^{20}\mathrm{D}_{\mathrm{REDD}t}\right)\frac{44}{12} \tag{2}$$

This emission reductions accounting is a static representation of the Bale Mountains. The methodology inherently assumes a steady state in mature forest, but this assumption is still under debate (Phillips et al. 1998, Houghton 2005, Bonan 2008, Grote et al. 2011). It is also assumed that all carbon in biomass is emitted to the atmosphere at the time of forest loss. This may overestimate emission reductions as harvested wood products such as housing and farm implements are manufactured (Karjalainen et al. 1999, Lim et al. 1999). However, with no consensus on how to account for harvested wood products, this assumption is necessary (Winjum et al. 1998).

Estimating revenues and REDD profits

Potential revenues under a REDD project scenario were calculated using the best- and worst-case emission reductions estimates. Discounted REDD profit is expressed by Eq. 3, where π_i is the profit in 2010 US$ over the 20-year lifespan project utilizing forest carbon stock estimates denoted by subscript *i*, $E_{t,i}$ are the emission reductions generated by the project in year t (tCO_2), *B* is a nontradable risk buffer of emission reductions expressed as a proportion, *p* is the price per ton of CO_2 in US$, *r* is the registry cost per ton of CO_2 in US$, *A* is the annual operating cost of the project in US$, δ is the discount rate, and *K* is the up-front costs (US$) of project establishment experienced in project year 1.

$$\prod_i = \left(\sum_{t=1}^{20} \frac{\left(\mathrm{E}_{t,i}(1-B)(p-r) \right) - A}{(1+\delta)^{t-1}} \right) - K \qquad (3)$$

The buffer accounts for the risk that emission reductions from forestry carbon projects may not persist over time, termed “nonpermanence,” or may be displaced, termed “leakage.” Permanence concerns arise because forest carbon stocks could deteriorate or be depleted over time due to natural disturbances such as fire, pests, and disease, or anthropogenic disturbances such as political instability (Sedjo and Marland 2003). Leakage concerns arise where emission-generating activities are relocated rather than reduced, leading to fewer, or even no, net emission reductions resulting from REDD project activities (Sohngen and Brown 2004). To deal with these nondelivery risks, a nontradable buffer, or reserve, of emission reductions is commonly set aside as insurance (Peskett et al. 2008). In this study, 40% of emission reductions was set aside for nonpermanence, and a further 25% of emission reductions was set aside for leakage. These buffers are at the higher ranges for project activities, and reflect imminent infrastructure development, a history of forest fire, and potential land tenure disputes and political instability in the Bale Mountains (UNIQUE 2010).

The remaining emission reductions were valued at predicted over-the-counter (OTC) VCM prices. While social costing of carbon would value emission reductions more highly at US$23 per ton of carbon dioxide equivalents (tCO_2e) (Tol 2008), the VCM is currently the only trading platform to realize the value of avoided deforestation. The VCM contracted by 47% in 2009, and there was an 11% decline in the price of emission reductions over all sectors following three years of steady growth. Emission reduction prices ranged from US$0.30 to US$111/tCO_2e, with an average price of US$6.50/$tCO_2e$ (Hamilton et al. 2010). Since 2009, OTC prices have stabilized around US$6/$tC0_2e$. The average price for REDD in 2009 was lower than the market average of US$2.9/$tCO_2e$ but increased to US$5/$tCO_2e$ in 2010, and ranged from US$1 to US$125/tCO_2e (Peters-Stanley et al. 2011). There is uncertainty in the price that can be expected for emission reductions from the Bale Mountains. Early interest in the project from buyers indicated that emission reductions could sell for US$3/$tCO_2e$ (UNIQUE 2010). If the Bale Mountains REDD project is certified to VCM standards, emissions reductions might receive a price premium; therefore, potential revenues were estimated using both US$3 and US$6.

Listing emission reductions in a public registry increases transparency within the VCM, and the costs of doing so, *r*, were estimated at $0.10/$tCO_2e$. Annual monitoring, verification, and operational costs of PFM, *A*, were estimated by forest carbon consultancy UNIQUE and the BERSMP at US$650,000 and subtracted from sales revenues. One-off project establishment costs in year one, *K*, were similarly estimated at US$3,225,000 (UNIQUE 2010). This cost includes establishment woodlots, 15 PFM units, project design documentation development, and validation to Voluntary Carbon Standards (UNIQUE 2010). While substantial, these cost estimates concur with existing literature on REDD project implementation costs (Cacho et al. 2005, Antinori and Sathaye 2007, Nepstad et al. 2007, WCS 2009). Resultant profits over the full 20-year REDD project lifespan were calculated in 2010 US$ using constant discount rates of 5% and 10% following Grieg-Gran (2006) and the Stern Review (Stern 2007). Because the details of revenue sharing between the various forest stakeholders are yet to be decided, profits are reported pre-tax and with no prior assumptions made about the returns to stakeholders. The uncertainties impacting REDD profits, as well as the method by which these uncertainties are addressed in this study, are summarized in Table 2.

RESULTS

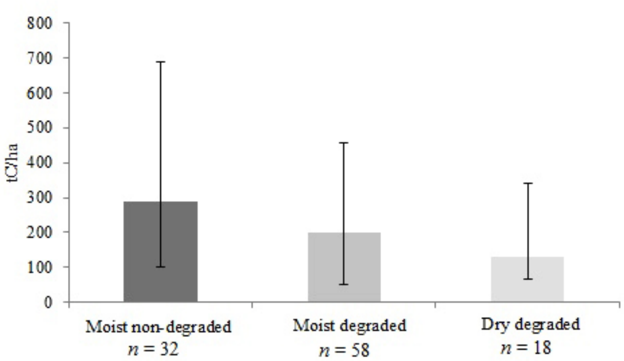
Within 108 forest plots, the dbh of 2698 trees was measured. An average of 35 trees per plot was found, with nondegraded moist forest (59) containing more than dry forest (20). Allometric equations applied to primary field data indicated forest carbon stocks of 289 tC/ha ± 108 (expressed as the 95% confidence interval of the mean) in moist nondegraded forest, followed by moist degraded forest at 199 tC/ha ± 54 and dry degraded forest at 132 tC/ha ± 73 (Fig. 2). Although forest carbon stock distribution was non-normal for all forest types

Table 2. Inputs and sources of uncertainty in profit assessment and methods by which uncertainty is dealt with in this study.

Input	Source of uncertainty	Method to deal with uncertainty	Values used
Project risk	Uncertain impact and success of project	A nontradable buffer of emission reductions is set aside to deal with leakage (Sohngen and Brown 2004) and nonpermanence (Sedjo and Marland 2003).	Under high project risks faced in the Bale Mountains, 25% of emission reductions are set aside for leakage and 40% for permanence nondelivery risk.
Carbon price	Subjective judgment, variability	Best guesses of over-the-counter voluntary carbon market prices are made given lack of price trends and the unclear future role of forestry emission reductions in climate policy.	The sensitivity to market price is assessed by modeling two carbon market prices: US\$3/tCO_2e and US\$6/tCO_2e.
Implementation costs	Subjective judgment, variability	Expert judgment of the implementing agencies in the Bale Mountains generated realistic cost estimates as implementation and transaction costs of REDD are often high and underappreciated (Grieg-Gran 2006, Antinori and Sathaye 2007, Nepstad et al. 2007, Boucher 2008, Böttcher et al. 2009).	Brokerage costs of 2.5% of emission reductions; registry costs of US\$0.1/tCO_2e; one-off costs of US\$3,225,000 to establish participatory forest management; and annual costs of US\$650,000, as predicted by UNIQUE (2010).
Discount rate	Subjective judgment, variability	The choice of discount rate follows best practice in environmental cost-benefit analysis and forestry (Weitzman 1998, Pearce et al. 2003, Groom et al. 2005, Hepburn and Koundouri 2007).	The sensitivity to discount rate is shown by modeling discount rates of both 5% and 10% following Greig-Gran (2006) of the Stern Review (Stern 2007).

(Shapiro-Wilks for moist nondegraded forest: n = 32, W = 0.77, p < 0.000; moist degraded forest: n = 58, W = 0.76, p < 0.000; dry forest: n = 18, W = 0.68, p < 0.000), a robust bootstrapped distribution that re-sampled with replacement 1000 times gave a very similar result to the normal approximation (Table 3). Nonparametric comparison of carbon stock showed a significant difference between forest types at the 5% level (Kruskall-Wallis, K = 6.942, df = 2105, p = 0.0311).

Fig. 2. Average forest carbon stocks in the Bale Mountains by forest type with 95% bootstrapped confidence intervals. The highest carbon stocks were found in moist non-degraded forest, followed by moist degraded and dry degraded forest.



The standard error of the forest carbon stock estimate was 19% in moist nondegraded forest, 14% in moist degraded, and 28% in dry degraded forest. The sampling error of the primary field data was, therefore, much higher than Chave et al.'s (2004) reported sampling error of 10% of the mean. However, the sample size of 108 plots was past the point where substantial gains in precision are made by increasing sample size (Fig. 3). Increasing the precision of the forest carbon stock estimate to 10% would require data from three times as many, or 347, forest plots. The confidence interval of the primary forest carbon stock estimate was also large, particularly for dry degraded forest, due to the small sample size (n = 18). High variation in above-ground forest carbon stocks due to variation in temperature, precipitation, and soil fertility has been observed in other studies but was not captured here (Houghton 2005). Signs of human disturbance were also observed in a number of plots, ranging from pathways to evidence of cattle grazing, although average canopy cover was greater than 50% in all forest types.

Area-weighted mean forest carbon stock across the forests of the Bale Mountains was 195 tC/ha ± 81. This is consistent with global forest ranges of 20–400 tC/ha reported by Hairiah et al. (2001), but higher than published Ethiopia-wide data of 37 tC/ha and 47 tC/ha (Brown 1997, FAO 2000). It is more comparable to the Africa-wide estimates of Gibbs et al. (2007) of 30–200 tC/ha, and of Lewis et al. (2009), who estimated average forest carbon stocks from permanent plots across Africa at 202 tC/ha. It is also comparable to smaller scale studies. Glenday (2006) found forest carbon stocks of 330 tC/ha in tropical moist forest in Kenya, although this included below-ground carbon stocks, and Munishi et al. (2010) found

Table 3. Bale Mountains forest carbon stock by forest type (tC/ha), comparing mean and confidence intervals between normal approximation and re-sampling with bootstrapped percentile confidence intervals.

	Mean and 95% confidence intervals					
		Bootstrap (1000 reps)				
Forest type	Normal approximation	*Mean*	*Upper CI*	*Lower CI*	Min.	Max.
Moist nondegraded (*n* = 32)	289 ± 108	289	187	400	0	1439
Moist degraded (*n* = 58)	199 ± 54	199	148	258	0	1024
Dry degraded (*n* = 18)	132 ± 73	132	66	208	25	569
All forest (weighted mean)	195 ± 81	195	120	278	0	1439

Fig. 3. Power curve showing the total number of forest plots required to accept the outcome with given level of confidence. The figure demonstrates that 108 forest plots achieve a power of 80%, or 20% precision, and that increasing this precision to 10% would require 347 forest plots to be surveyed.

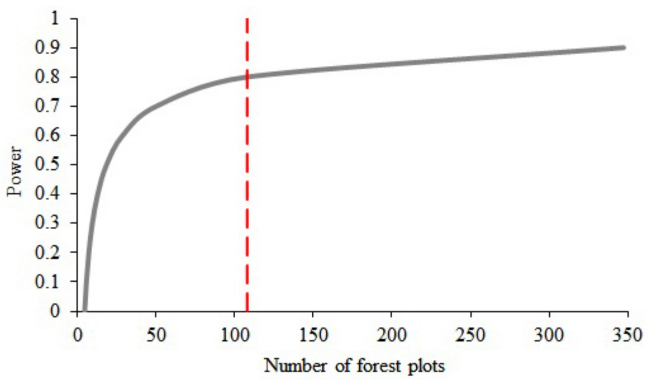
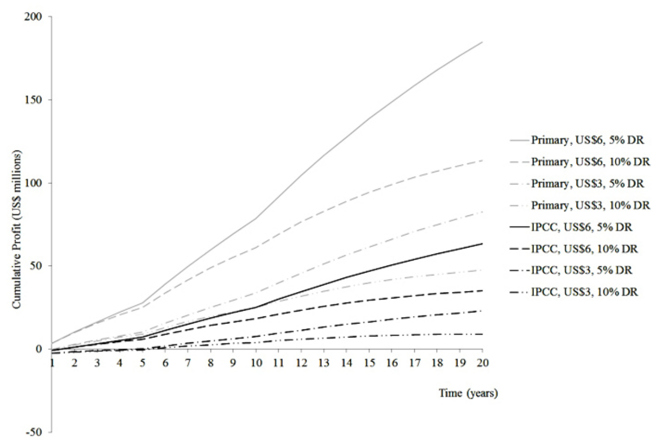


Fig. 4. Estimated cumulative profits over the Bale Mountains REDD project lifespan showing primary and secondary IPCC data under variable carbon price and discount rates (DR).



comparable tropical moist forest in the Eastern Arc Mountains of Tanzania to be in the range of 252–581 tC/ha. As Baccini et al. (2008) note in their mapping of above-ground biomass in Africa, the continent is very diverse, hosting a wide range of ecosystems that explain variation in biomass and carbon content. Comparing primary data forest carbon stock estimates to biome-averaged and IPCC defaults, in both moist and dry forest, the secondary data are within the lower bound of the primary data confidence interval. Biome-averaged data would, however, underestimate the mean moist forest carbon stock of the Bale Mountains by between 47% and 63% and dry forest carbon stock by an average of 56% (Table 4).

Cumulative emission reductions generated over the 20-year project lifespan based on primary data are twice those generated using IPCC data: 180,272 $ktCO_2$ compared to between 71,305 and 89,723 $ktCO_2$ using ecological zone and Africa-specific data, respectively. This result is comparable to the 144% difference between emission reductions using five forest carbon stock estimates in Panamanian forest (Pelletier et al. 2010). Over the forested project area, positive net revenues are generated under all forest carbon stocks. Primary data estimates generate between US$115 and US$445 per hectare, and IPCC ecological zone data, the lower of the two IPCC estimates, return US$21 to US$152 per hectare. The differences between forest carbon stock methods are marked; in the worst-case scenario using secondary data, US$3/$tCO_2$e and a 10% discount rate, the project does not break even until year 6 (Fig. 4). At a conservative market price of US$3/$tCO_2$e and a 10% discount rate, primary data suggest that a REDD project in the Bale Mountains could generated US$48 million compared to US$9 million using IPCC data (Table 5).

DISCUSSION AND CONCLUSION

Comparing primary data from the Bale Mountains to biome-averaged forest carbon stocks reported by the IPCC reveals discrepancies higher than the 44% for African rain forest reported in GOFC-GOLD (2008). It supports findings that the application of biome-averaged data tends to underestimate

Table 4. Comparison of primary data from this study with secondary above-ground forest carbon stock data, by forest type, showing the discrepancy between forest carbon stock methods (tC/ha). Secondary data sourced from IPCC (2006); note that the ecological zone data have only a point estimate.

	Primary data	Ecological zone specific		Africa specific	
Forest classification	tC/ha	tC/ha	As a % of primary data	tC/ha	As a % of primary data
Tropical moist	231 (179–283)	85 (-)	-63%	122 (75–202)	-47%
Tropical dry	132 (59–205)	61 (-)	-54%	56 (56–61)	-58%

forest carbon stocks as compared to local-level estimates (Grassi et al. 2008, Pelletier et al. 2010, Preece et al. 2012). Primary data reveal high uncertainty surrounding the use of mean estimates. The 95% confidence intervals for primary forest carbon stock estimates are, on average, 39% of the forest strata mean. The large uncertainty results in the overlap of the lower confidence interval bounds of primary data with the upper bounds of the interval around the IPCC estimates. These results suggest that diversity of forests is not sufficiently captured by the 20 ecological zones and four climate domains encompassed by the IPCC data. While our focus is on the impact of forest carbon stocks, it should be recognized that uncertainty in other aspects of the forest carbon stock and in emission reductions accounting, such as the stratification of forest area, application of allometric equations, carbon fraction, forest area estimates, and generation of the baseline will serve to further increase and compound uncertainty as would the inclusion of other carbon pools, such as the below-ground biomass of tree roots or soil carbon (Waggoner 2009, Ciais et al. 2011). In particular, forest area change under the project—activity data—will need to be collected, whereas here it is based on projected deforestation goals of the PFM project. The method used to gather and analyze this activity data will also impact the error of the emission reductions estimate (Achard et al. 2007, Duveiller et al. 2008). Further research is required to understand if additional sources of uncertainties act to reduce or increase estimates of forest carbon stocks, as well as to consider how emission reductions accounting is carried out for the suite of REDD activities that go beyond avoided deforestation.

The discrepancy between carbon stock estimates leads to more than a two-fold difference in emission reductions from a REDD project in the Bale Mountains, a substantial amount in potential profits. This highlights research needs for forest carbon stock methods using local data despite the fact that emissions accounting using biome-averaged data can be undertaken immediately for low or no cost, making them an attractive option. We demonstrate a financial incentive for investing in the capacity to gather primary data. With the popularity of REDD partially dependent on the transfer of finance from developed to developing countries, more complex accounting can also ensure that rewards for reducing deforestation and degradation are of appropriate scale. However, with costs of reducing uncertainty rising as methods become more data intensive, trade-offs may emerge. The costs of increasing the statistical power of forest carbon stock estimates, for example, may be greater than the benefits of improved estimates given diminishing returns in sampling effort. Tools such as sensitivity analysis could be employed to identify components with the most impact on total uncertainty which can then be prioritized (Elston 1992).

Financial analysis is commonplace to guide decisions to implement REDD projects. If estimated revenues are insufficient to meet cost demands of REDD, then other tools to fund forest conservation might be considered (e.g., Morse et al. 2009, Fisher et al. 2011). Conversely, climate change mitigation potential may be lost where emission reductions are more substantial than a feasibility assessment would indicate. All scenarios of the Bale Mountains REDD project predicted net positive profits at year 20, despite underlying differences in forest carbon stocks and VCM prices. Low returns to investment and a long return period, however, may not be sufficient to justify investment in the high up-front costs of REDD. Our financial calculation does not include taxes to federal and regional government or consider the share of payments between numerous forest stakeholders. These details are likely to make the cost-to-benefit ratio even less favorable. Given that finance for forest conservation in the Bale Mountains is low and largely donor funded, however, even small net positive revenues may be a sufficient argument for implementing REDD. As noted in Potapov et al. (2008), forests are important for a variety of purposes. The Bale Mountains is an area of high biodiversity value that supports numerous livelihoods and provides water to many downstream users; thus, other ecosystem services will be generated from avoided deforestation, which might factor into decision-making (BMNP 2007). Using PFM to generate REDD may also shift forest resource use onto a sustainable pathway, supporting livelihoods and contributing towards clarifying property and forest-use rights for local peoples. Decisions on whether to implement REDD may therefore not rely completely on financial feasibility analyses. This decoupling of REDD policy decisions and cost-benefit analysis is evidenced by cases where the costs of REDD project and

Table 5. Net present value of profits under different forest carbon stock methods calculated by subtracting the costs of REDD project implementation from revenues generated through sale of emission reductions. Two price scenarios, US$3 and US$6, and two discount rates (5% and 10%) are presented and net profits are given in 2010 US$.

	Primary data				Ecological zone IPCC default			
Carbon price	*US$6*		*US$3*		*US$6*		*US$3*	
Discount rate	*5%*	*10%*	*5%*	*10%*	*5%*	*10%*	*5%*	*10%*
Profit US$ (000)	184,978	113,607	82,671	47,591	63,359	35,129	22,893	9017
Profit US$/ha project area	445	273	199	115	152	85	55	21

policy development are being absorbed by intermediaries or met through donor finance (Watson and Nakhooda 2012).

Many national forest inventories in developing countries are not comprehensive, and limited resources exist for new field measurement (DeFries et al. 2006). The implications of the discrepancy in forest carbon stocks makes the case for earmarking existing REDD finance flows to build the capacity of developing countries to prepare for a future UNFCCC mechanism, for reducing uncertainty and improving national forest inventories through long-term institutional backing and resources. Not only for forest carbon stocks, support could ensure that developing country governments benefit from advances in satellite imagery and improved understanding of emission reductions leakage, which may be more appropriate at a national rather than project level. Improving data on forest monitoring is important regardless of the ultimate financing mechanism for REDD and will serve to reduce the distance between broad averages and spatially limited estimates (Grainger 2010). While we have provided a static assessment of forest carbon stocks, it is also worth noting that a functioning REDD project will require performance to be assessed on an ongoing basis. Ongoing assessments will reduce uncertainties in forest carbon stocks, and when applied to community forestry it can also capture forest carbon stock changes resulting from degradation in addition to deforestation (Skutsch et al. 2011). As implementing REDD through PFM gains prominence, particularly in East Africa (Klooster and Masera 2000, Murdiyarso and Skutsch 2006, Agrawal and Angelsen 2009, Hayes and Persha 2010, Mustalahti et al. 2012), earmarked finance might also be directed to broadening research into linking community forestry with tropical forest science and community-level forest monitoring (Michon et al. 2007, Somanathan et al. 2009, Skutsch and Ba 2010).

We emphasize the financial implications of uncertainty in emission reductions accounting for REDD projects. When biome-averaged carbon stock estimates are compared with estimates established from direct tree measurements, the financial discrepancy is sizeable. If such discrepancies become commonplace, they could call into question the environmental integrity of REDD. Uncertainty may also generate unrealistic expectations of profits that erode the credibility and potential of the mechanism. Delivering REDD has proven more complicated than many initially thought (Watson and Nakhooda 2012), and these findings demonstrate the need to improve the quantification of uncertainty in forest carbon stocks, reduce uncertainty where possible, and communicate uncertainty in a way that can be utilized in policy decisions. Reducing reliance on the conservativeness principle could aid this shift. While conservativeness will remain important to ensure emission reductions are not underestimated in the reference period and overestimated in the assessment period, it should not preclude efforts to reduce forest carbon stock uncertainties. Dealing with decision-making under uncertainty is not novel in climate change policy (Webster et al. 2002), and presently, countries are encouraged but not obliged to include uncertainty estimates in their national communications to the UNFCCC (UNFCCC 2002). While highly uncertain GHG accounting might be acceptable for national communications, it is insufficient for a performance-based incentive mechanism like REDD. Although additional costs will be incurred to reduce uncertainty, and trade-offs between factors in the accounting process may be introduced, the financial incentives for improved emission reductions accounting are clear.

Responses to this article can be read online at:
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