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A novel application of satellite radar data: measuring carbon sequestration and detecting degradation in a community forestry project in Mozambique

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Abstract

Background: It is essential that systems for measuring changes in carbon stocks for Reducing Emissions from Deforestation and Degradation (REDD) projects are accurate, reliable and low-cost. Widely used systems involving classifying optical satellite data can underestimate degradation, and by classifying the landscape ignore the natural heterogeneity of biomass.

Aims: To assess the ability of repeat L-band radar to detect areas of small increases or decreases in aboveground biomass (AGB) across a Miombo woodland landscape.

Methods: ALOS PALSAR L-band cross-polarised (HV) radar data from 2007 and 2009 were used to create maps of AGB, calibrated using 58 field plots. The change in AGB was assessed for land parcels with known landcover histories: (i) 500 ha of new agroforestry; (ii) 9500 ha of protected (REDD) areas; and (iii) 23 ha of land where degradation occurred between 2007 and 2009.

Results: Increases in AGB were detected in both the agroforestry and REDD areas (0.4 and 1.1 Mg C ha^{-1} $year^{-1}$ respectively); while the degraded areas showed a decrease of 3 Mg C ha^{-1} $year^{-1}$.

Conclusions: PALSAR data can be used to detect losses and gains in AGB in woodland ecosystems. However further work is needed to precisely quantify the uncertainties in the change estimates, and the extent of false-positive and false-negative change detections that would result from using such a system.

Keywords: Africa; aboveground biomass; community forestry; forest monitoring; Miombo; Radar; REDD; REDD+; remote sensing; SAR; savanna; woodland

1. Introduction

Since the Reducing Emissions from Deforestation and forest Degradation (REDD, more recently also known as REDD+ or REDD++) framework was first discussed in the UN climate negotiations at Bonn in 2005 (UNFCCC 2005), a number of projects have been set up using a similar conceptual idea, but according to various standards associated with the voluntary carbon market (FAO, 2010). The number of such projects is set to increase markedly in the coming years, and they will form essential case studies informing the large-scale implementation of REDD that is likely to eventually occur following the agreement to implement REDD globally at the UNFCCC Conference of Parties meeting in Cancun in December 2010 (UNFCCC 2010). Although there are many potential benefits to REDD, including reducing land use change emissions, the loss of biodiversity and ecosystem services from the world's forests, and increasing the standard of living and opportunities for the world's most vulnerable people, this potential will only be realised if REDD is correctly formulated. There are a number of difficult problems still to be addressed, each with the capacity to reduce the net benefit of the whole scheme.

One key issue is how carbon stocks and changes in these stocks will be assessed. The international REDD process is developing a comprehensive methodology for setting reference emission levels at a national level, involving both historical deforestation rates and socio-economic modelling. However, working at the project level, the voluntary carbon market awards credits based on the subtraction of the actual with-project net emissions from a 'baseline' scenario. This baseline scenario is an estimate of how much carbon would have been lost from the project area in the absence of the REDD activities. This baseline deforestation rate is often calculated using past deforestation rates (calculated from field data, remote sensing, or published regional or national averages), combined with modelling approaches using economic and social data to predict future rates, but there is currently little knowledge of which method produces the most accurate estimate of historical deforestation rates, nor the optimum method for measuring current carbon stocks, a necessity for carbon credits to be awarded (GOFC-GOLD 2009).

Traditional remote sensing systems for measuring deforestation are based on the classification of high resolution optical data into polygons, a system exemplified by that used by Brazil's National Institute for Space Research (INPE) to track deforestation in the Brazilian Amazon (Hansen et al. 2008). However such methodologies may not be suitable for REDD, as they do not necessarily detect small-scale deforestation, and cannot normally directly detect degradation (different definitions are used for forest degradation in different contexts (IPCC 2003), but in a REDD context it can be defined as the anthropogenic loss of biomass from within a forested area that remains forest under the relevant national definition after the degradation has occurred). Though the DETEX & DEGRAD programmes of INPE are mapping selective logging and degradation using optical data, they can only detect degradation in areas greater than 6.25 ha, much larger than much of the degradation occurring in Africa, and even then have a successful detection rate of only 50% (Sato et al. 2011). Using optical data to detect degradation is hard because the loss of canopy cover caused by degradation is normally both small and short-lived (Lu et al. 2005).

A plethora of different methods have been used for baseline calculations by voluntary REDD projects. To assess this we have reviewed different methodologies used by the seven voluntary REDD projects approved (at the time of writing) by the Climate Community & Biodiversity Alliance (CCBA), a leading standard for certifying the social and environmental benefits of voluntary carbon reduction projects. It can be seen that every one of these projects uses a different methodology to assess their baselines (Table 1). However, within the Project Design

Documents (PDDs) for each project there is often very little (or no) justification as to why that particular method is believed appropriate for their case, and in none of the PDDs has any attempt been made to assess how the results would differ with a different method.

One area of consistency within these projects is that six of the seven studies use medium/high-resolution optical imagery (predominantly 30 m resolution Landsat, but also in one case 10 m resolution SPOT) to estimate the baseline deforestation rate, with standard average biomass values for each landcover-type being used to convert this into emissions (as recommended by UNFCCC 2005). Such data are used because they are relatively simple to interpret and widely available at a low cost. However, they are not ideal for REDD because their resolution is too coarse to detect degradation in most cases, and the season of the image and current water status of the vegetation can confuse the interpretation of change (Lu 2004; Mitchard et al. 2009a). This latter problem is especially problematic in lower biomass regions, where the phenology of grasses, shrubs and trees all differ markedly over the season (Lu 2006). Equally, the very system of classifying the landscape into distinct classes, each given an average biomass value, can induce very large errors by over-simplification: tropical forests, woodlands and savannas are all highly heterogeneous in biomass values at the small-scale at which deforestation and degradation commonly acts (Scholes et al. 1997; Chave et al. 2004; Ryan et al. 2011a). For example, in the Miombo woodland areas of Mozambique, where this project is based, the landscape is a continuum from high biomass mature Miombo right through to grasslands with scattered trees, with all vegetation anthropogenically influenced to some extent (Williams et al. 2008). We believe that in such situations, in order to set up a baseline deforestation/degradation rate, and to measure the current carbon stocks as the project proceeds, it would be much better to estimate the above-ground biomass (AGB) value of every pixel and update this through time. We test such an approach in this paper.

To our knowledge, no REDD project has yet used satellite-based radar to measure changes in AGB, and thus to calculate baseline deforestation rates, and changes in forest biomass. This is despite the strong relationship that is known to exist between radar backscatter and biomass in tropical ecosystems (Mitchard et al. 2009b), and its known ability to detect deforestation (Thiel et al. 2006; Santoro et al. 2010). The lack of use of radar is in part due to the saturation of the radar response to AGB, at around 150 Mg ha^{-1} for cross-polarised L-band radar data (Mitchard et al. 2009b); however this AGB value is easily high enough to cover the full range of observed biomass values in dry tropical biomes, and to detect changes in biomass in deforested areas, and secondary forest in wetter systems. Satellite radar has an additional advantage over optical data: the signal is not obscured by cloud, enabling the production of consistent time series over large areas, which is often not possible with optical data in the tropics. There is a perception that radar data are more difficult to acquire and process than optical data, but we believe the processing chain described in this paper is not difficult, and recent initiatives, such as the JAXA Kyoto and Carbon Initiative provide pre-processed radar data at no cost to the user.
(http://www.eorc.jaxa.jp/ALOS/en/kc_mosaic/kc_mosaic.htm)

In this paper we use a unique ground dataset including extensive forest plots and information on areas of tree planting, forest protection and degradation to examine the accuracy of a simple methodology using satellite radar backscatter scenes from two different dates. Using a relationship between the forest inventory biomass plot data and radar backscatter, we produce biomass maps from both dates and attempt to track deforestation, degradation and carbon sequestration, and estimate the uncertainty of the detected changes.

2. Materials and Methods

Study Area

The Gorongosa Community Carbon Project is located in central Mozambique in the buffer zone of the Gorongosa National Park (18°46'S 34°30'E), and has been running since 2003 as a voluntary-sector carbon forestry project involving using agroforestry and reduced deforestation (REDD) activities. It is certified by Plan Vivo, a community standard, based around long-term land use change for carbon sequestration, and social, environmental and biodiversity benefits (www.planvivo.org). It is currently managed by Envirotrade (Grace et al. 2010). It began as a pilot scheme of 20,000 ha, but has since been expanded to 56,000 ha.

The principal landcover type of the area is Miombo woodland, with other areas of more open savanna and shifting agriculture, as well as some gallery forest near rivers. Most of the woodlands are burned regularly or semi-regularly, though there is a wide mosaic of different fire revisit times across the landscape (Ryan et al. 2011b). For the years 1956-1969 and 1998-2007 good quality rainfall data are available from Chitengo meteorological station 25 km to the east of Nhambita. These data yield a mean annual rainfall of 850 mm, with a standard deviation of 269 mm (Ryan 2009); there is a strong but variable dry season from April-October, with May-September receiving on average less than 20 mm of rain per month (Ryan 2009). The soils are highly weathered sandy loams or sandy silt loams (Ryan et al. 2011b).

Most farming in the area concentrates around ‘machambas’ – clearings of 1-2 ha in which crops such as maize (*Zea mays* L.), cassava (*Manihot esculenta* Crantz) and sorghum (*Sorghum bicolor* (L.) Moench) are grown for a few years (Williams et al. 2008). The project activities have concentrated on planting trees within these ‘machambas’ (‘agroforestry areas’), and also protecting large areas of Miombo woodland entirely from deforestation (‘REDD areas’). The agroforestry activities have taken a variety of forms, with the nitrogen-fixing legumes *Faidherbia albida* (Del.) A. Chev. and *Gliricidia sepium* Kunth being planted within *machambas* between crops to provide shade and improve the soil, and cashew (*Anacardium occidentale* L.) and mango (*Mangifera indica* L.) planted for their nuts/fruits, and in both cases providing voluntary carbon credits to the project participants.

These agroforestry and REDD areas have been accurately mapped, as have some areas of known degradation. Additionally, as part of the scientific and monitoring efforts within the area a number of field sites have been established. This makes the region ideal for testing how well radar data can be used to detect biomass change in these different areas.

Field data

Biomass plots. A number of permanent and temporary vegetation plots have been set up since the project started. In order to create a ground database to calibrate the response of radar backscatter to AGB, we selected 58 plots, namely those that were measured between 2005 and 2009 and are believed to have been undisturbed since they were measured (Figure 1). These included two types of plots: firstly, there are 15 square plots of 1 ha each, eight triangular plots of 0.28 ha, and five circular plots of 0.5 ha, measured from 2005-2007. For these plots all live stems with a diameter at breast height (1.3 m, DBH) greater than 5 cm were inventoried. Secondly, 30 plots were measured in 2009. These are 125 m x 50 m, essentially rectangular but with rounded ends, with an area of 0.57 ha. All stems with a DBH > 30 cm were measured for the whole plot, and all stems > 5 cm were additionally measured for three 20 m diameter circular subplots within the main plots (Figure 1 for detail of the shape).

AGB was calculated from DBH for all the plots using an allometric equation developed from destructive harvesting of 29 trees from the site (Ryan et al. 2011a):

$$B = \mathrm{EXP}[2.601(\ln(\mathrm{D}_{\mathrm{BH}})) - 3.629] \qquad (1)$$

Where B = Aboveground biomass (Kg C) and D_{BH} = DBH (cm). For the thirty plots where stems in the range 5 - 30 cm were only measured for subplots, correction was needed to calculate the AGB of the whole plot. To do this the total AGB for stems from 5-30 cm DBH were multiplied by 6.06, the ratio between the area of the subplots and the total plot area, and added to the AGB calculated for stems > 30 cm.

Areas of known agroforestry, REDD and degradation

Trees have been planted by farmers in the area since the carbon sequestration project started in 2003. The boundaries of every agroforestry site have been recorded by GPS, along with the type of planting that has been credited. For the purposes of this project we used all the 546 land parcels (average size 0.92 ha) where important tree planting had taken place, involving the planting of native trees, timber trees or fruit trees. Credits have also been earned by farmers in the project through 'border planting', involving planting trees around the edges of their 'machambas'. We chose to exclude these from the analysis as such planting would be unlikely to significantly affect the biomass of the whole parcel. We also investigated 38 REDD areas (average size 250 ha), where no new 'machambas' should have been created and no significant deforestation or degradation should have occurred.

Additionally, six areas where degradation is known to have occurred between 2007 and 2009 had their outlines recorded using GPS data in 2010. These were not clear-cut, but had an important (but unquantified) portion of their AGB removed, either for agriculture or for the installation of power lines. These had an average size of 3.5 ha.

Remote Sensing Data

Synthetic Aperture Radar (SAR) data were collected over the field site in 2007 and 2009 from the Phased Array L-band Synthetic Aperture Radar (PALSAR) sensor on the Advanced Land Observing Satellite (ALOS) (Table 2), with two scenes needed to cover the field site at each date. These scenes were captured in the Fine-Beam Dual (FBD) mode, which has an incidence angle of 34.3°, a ground resolution of ~20 m, and collects in both Horizontal-send Horizontal-receive (HH) and cross-polarised, Horizontal-send Vertical-receive (HV) modes.

The scenes were processed, terrain-corrected and converted to σ^0 ('sigma-nought', normalised backscatter coefficient scaled to a log-based dB [decibel] scale) using MapReady 2.3.6 (Alaska Satellite Facility), all at a resolution of 25 m. For terrain-correction we used the 90-m resolution Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) processed by the CGIAR Consortium for Spatial Information (http://srtm.csi.cgiar.org/). All subsequent remote sensing analysis was performed using ENVI 4.7 (ITT Systems). The scenes were joined together, with analysis of the join showing no varation in geolocation or brightness despite the difference in month of capture for the two scenes in both cases (Table 2). To ensure accurate geolocation with ground points they were warped to a 30 m resolution Landsat 7 L1T scene from 5 May 2003 (L71167073_07320030513), using a network of 62 ground control points from permanent features such as road junctions and islands, with a Root Mean Squared Error (RMSE) of 14.2 m.

Data analysis

It has been shown previously that PALSAR HV data relate strongly to AGB in this site (Mitchard et al. 2009b). We therefore intended to use the pseudo-invariant biomass plots to calibrate the PALSAR HV data to create biomass maps for both 2007 and 2009, and then to compare these maps for the specific areas under the three different known land-use trajectories.

The σ^0 values for individual 25 m pixels covering the field sites were converted to power (m^2/m^2) before averaging, so the arithmetic rather than geometric means were used in later calculations. As errors exist on both axes we used a Reduced Major Axis (RMA, i.e. Type II) regression, as this was seen as more appropriate than ordinary least squares (OLS, i.e. Type I) regression, for which we would have to assume that the ground data has negligible error. This has not commonly been applied to remote sensing data, but we believe the extensive errors involved in ground estimation from small field plots make it a necessity (Chave et al. 2004). The AGB data were log-transformed, allowing a linear relationships between log(AGB) and σ^0 to be fitted. All statistical analyses were performed using R 2.11. In order to confirm that the results were not due to artefacts inherent in the methodology, an alternative method was also used, involving the cross-calibration of the 2009 scene to 2007 using near-invariant targets. The methods and results of this alternative analysis are presented in Appendix A. A further test was also performed to assess the significance of the choice of RMA over OLS regression on the overall change results.

The field data inventory dates varied from 2004-2009 for the different plots, and the radar data from two dates, 2007 and 2009; however due to the limited field data the same field data were used for both time points. It is not believed that the AGB of the field plots has changed much during this period (they have not been deforested, L.E. Goodman and C. Ryan pers. comm., and the growth rates of woodland in the area have been shown to be at most ~0.7 Mg C ha^{-1} year^{-1} (Williams et al. 2008), at the limit of what could be detected by radar). No correction was made for growth in the plots due to the large number of assumptions that would be necessary, due to their different landcover types and histories, soil characteristics, and year of survey: the AGB plots were assumed for the purpose of this analysis to be pseudo-invariant. The AGB-backscattter equations were applied to the remote sensing data after it had been averaged to 100 m pixels, in order to reduce speckle noise, and reduce the impact of any slight geolocation inaccuracies on the change detection. These maps were limited at 60 Mg C ha^{-1}, as this biomass value is thought to be around the highest possible in the area (the highest biomass in our field dataset is 51.3 Mg C ha^{-1}, though higher values might be possible in riverine forest areas), and is also close to the useful limit of L-band radar's sensitivity to AGB (Mitchard et al. 2009b; Mitchard et al. 2011a).

Finally, the changes in AGB in the agroforestry, degraded and REDD parcels were compared between the two time points. From this, an assessment was made as to whether radar would be a suitable system for measuring change in AGB for this site.

3. Results

AGB to radar backscatter relationships

Significant relationships between HV radar backscatter and AGB were found for both years (Figure 2). The fitted relationships (fitted using RMA regressions between log-AGB and σ^0) were of the form:

$$\sigma^0_{HV} = a + b(\log(B)) \qquad (2)$$

Which was rearranged to:

$$B = 10 \wedge \left[\frac{\sigma^0_{HV} - a}{b} \right] \qquad (3)$$

with coefficients (± 95 % confidence intervals), r^2, P-value, and (RMSE) for the fits:

2007: a = -28.45 ± 0.96; b = 7.65 ± 0.72; r^2 = 0.64; P < 0.0001; RMSE = 6.4 Mg C ha$^{-1;}$; 2009: a = -26.42 ± 1.12; b = 8.14 ± 0.83; r^2 = 0.60; P < 0.0001; RMSE = 6.3 Mg C ha^{-1}.

An ANCOVA analysis was performed to test if these two regression lines were significantly different. The test found that the slopes were not significantly different (P = 0.85), but the intercepts were different ($P < 0.0001$). The value of this difference in intercept (or 'gain') was 2.03 ± 0.18 (standard error), and is shown graphically in Figure 3, which displays the pairs of backscatter values for each ground plot, with an RMA regression line fitted. This difference could be due to calibration issues in the radar product or due to different soil or vegetation moisture conditions between the two dates. Therefore, for the principal methodology the two equations were applied individually to each year to produce biomass maps, as applying the same relationship would have reduced accuracy by not incorporating the difference in response between backscatter and biomass in the two dates.

In order to confirm that using different equations for each time point was not introducing a bias, an alternative analysis is presented in Appendix A. This uses invariant targets to cross-calibrate the radar data from 2009 to the 2007 data. This alternative methodology produces very similar results to that using the primary analysis. A further analysis was performed to test that the use of RMA (Type II) regression rather than OLS (Type I) did not significantly change the results. Though the fits produced were statistically significantly different (parameters for Equations 2 & 3: 2007: a = -26.48, b = 6.11; 2009: a=-24.04, b=6.63), resulting in small consistent changes in the absolute pixel values of the biomass maps produced, the mean estimates for the AGB change values differed by less than 1 % for all three landcover classes.

AGB change

The changes within each class are summarised in Table 3 and Figure 4 (and are similar to those found with the alternative methodology; see Appendix A). AGB in the 500 ha of agroforestry parcels had a detected increase in biomass of +0.74 Mg C ha^{-1} over the 2-year period. There were marked differences among the parcels, with many parcels losing AGB, and some gaining much larger amounts (Figure 4). The increase in the REDD areas was unexpectedly higher than for the areas with active tree planting, at + 2.2 Mg C ha^{-1}, again with high variability. For the six areas that underwent degradation between 2007 and 2009, a major loss of biomass was observed. This loss over the two years averaged 6.1 Mg C ha^{-1}, representing approximately 20% of the original biomass.

In the absence of field data giving the true values of gains and losses in these known land-use parcels, calculating uncertainties associated with these change values is difficult. We believe the best estimate for the accuracy of absolute values is to use the RMSE values for the calibration equations for that date (Equations 2 and 3), and for change detection at a pixel level the best approach is to use the value of the RMSE of the difference of the predicted AGB values of the field plots for the two dates, which is ±3.1 Mg C ha^{-1}. This RMSE value is larger in magnitude than the increases seen in the REDD and agroforestry areas, questioning the validity of the observed increases; but is smaller than the detected decrease in the known degraded areas.

4. Discussion

These results show that satellite radar data can be used to measure changes in AGB for projects involving forest preservation (REDD) and afforestation/reforestation activities. Degradation is clearly detected (Figure 4), and the areas known to have been protected or to have been subject to tree planting show small increases in estimated AGB, though the mean of these increases is smaller in value than the uncertainty level estimated for the change detection, so we cannot confidently conclude that these areas have changed in AGB. However, this uncertainty value was derived at the plot level, and thus may be too conservative as uncertainties decrease when larger areas are considered (see Section 5.1). In addition to the number and size of three-dimensional scatterers (which correlate with AGB), the radar signal is influenced by radar noise, slight geolocation errors, and moisture in vegetation and in the soil. Therefore we suspect that small changes, such as increases in AGB through the growth of trees over a 2-year period, can only be confidently detected by averaging many pixels. Therefore radar analysis should not be used in isolation to quantify emissions reductions (leading to payments) at a fine scale or over short time-periods, but can be used for monitoring at the project scale, in particular to provide a frequent (e.g. annual) estimate of the carbon balance of a project area (including deforestation/degradation and regrowth).

Uncertainty: absolute AGB values and change detection

The finding of a difference in the AGB-backscatter relationship between the 2 years could have important consequences for using radar data. The strong linear relationship found in the cross-calibration procedure with the suspected near-invariant targets (Appendix A) suggests that a calibration difference be the most likely cause, but changes in vegetation/soil moisture could also have caused a consistent difference in backscatter. This finding should not affect the uncertainty associated with the results, but stresses the need for field data (ideally concurrently with the capture of the radar scene) for interpreting radar data: applying AGB-backscatter relationships without field plot data is not recommended, and thus simple change-detection algorithms relying directly on changes in radar backscatter should not be used to detect deforestation (c.f. Santoro et al. 2010). At the very least, cross-calibration with invariant targets should be used before the radar backscatter values are compared at a pixel or parcel level. We suspect that the equations relating AGB to HV backscatter are not substantially different between time-points and sites (Mitchard et al. 2009), but accuracy will always be increased with local field data.

Ideally, overall uncertainty in this kind of analysis would be quantified by propagating errors from every stage of the analysis through to the final estimates (GOFC-GOLD 2009; IPCC 2000). This was attempted using similar data in Mitchard et al. (2011a,b), but the available ground data here were not sufficient to allow such estimation to proceed. The uncertainty in the estimation of AGB from the DBH, species and height data measured in the field plots, and the locally-derived allometric equation, is estimated in Williams et al. (2008) and Ryan et al. (2011b). However, the uncertainties in this analysis, assuming the ground plots represent true AGB values, are produced from a number of sources that are hard to quantify, including: geolocation inaccuracies in relating the field plots to the radar pixels; temporal decorrelation between the collection of the field data and the timing of the two radar acquisition dates; random noise in the radar data; and radar data response to factors unrelated to AGB, for example ground roughness and moisture. Instead of trying to estimate the uncertainties relating to each of these factors individually, we use our ground data to give the Root Mean Square Error (RMSE), a non-parametric estimate of accuracy, or strictly the average deviation of a predicted point from its true value (GOFC-GOLD, 2009). The RMSE from the original calibrations from the field plots is 6.4 Mg C ha^{-1} for 2007 and 6.3 Mg C ha^{-1} for 2009, or equivalent to ±22.2% and ±21.8% of the mean AGB of the field plots (28.7 Mg C ha^{-1}) respectively. These values are used below as estimates of accuracy at the 1 ha level, though the average plot size is 0.64 ha, so this is probably an overestimate of the true uncertainty.

We first use the RMSE value to estimate the accuracy of a measured change in AGB at the level of a single 1 ha pixel. If the errors associated with both measurements are assumed to be independent (the most conservative scenario), then estimates of change can be calculated using a Tier 1 equation for calculating differences in carbon stocks between years (IPCC 2003: Table 6.1 Column M, GOFC-GOLD 2009: Table 2.6.1 Column G). This equation is:

$$U_{total} = \sqrt{(U_1)^2 + (U_2)^2} \qquad (5)$$

Where U_{total} is the percentage uncertainty in the difference of the quantities and U_i is the uncertainty related to the original quantities (here estimated as the RMSE divided by the mean). Applying this equation to the data gives an uncertainty for the difference of ±31.1%, or ±9 Mg C ha^{-1}.

Using this assumption suggests that this method should only be able to reliably and confidently detect very large gains or losses of AGB at this spatial and temporal resolution (in fact only losses, as over a 2-year period gains of more than 9 Mg C ha^{-1} are ecologically unrealistic). There is, however, some evidence from the dataset that the errors in repeat measurements are not independent, decreasing the value of the smallest AGB change that can be reliably detected at the plot level. This is as we would expect, as some of the error inherent in the RMSE is due to local vegetation and terrain conditions, which do not change as much from year to year, in comparison with moisture and radar noise (Mitchard et al. 2011a). This evidence derives from the RMSE calculated by subtracting the AGB values estimated for the plots using the radar data from 2009 with the AGB estimated from the same plots using the radar data from 2007. This analysis is only valid if the AGB values of the field plots were effectively unchanged over the 2-year period; based on our knowledge of the plots we believe this assumption is reasonable. This RMSE values is 3.1 Mg C ha^{-1}, which is approximately a third of the accuracy calculated from Equation 5. This suggests that due to correlated errors, changes greater than ±10.7 %, or ±3.1 Mg C ha^{-1}, should be detectable at a 1 ha resolution, which is low enough to detect degradation with confidence, and regrowth over longer time periods.

While we believe this estimate of ±3.1 Mg C ha^{-1} represents the best figure for the accuracy of the change estimates, it was derived at the plot level, and there are reasons to believe that uncertainties in change estimates decrease as larger areas are considered. This is because it has been postulated that errors in change detection are random, and that systematic biases in the original processing steps cancel out (Mitchard et al. 2011a). This applies only to change estimates, and only when large numbers of pixels are considered: this is because errors that can introduce biases, for example errors in allometric equations, should affect both AGB estimates approximately equally, cancelling out when one is subtracted from the other (Mitchard et al. 2011a). This assumption would allow the change values derived from radar to be considered more accurate when many pixels are summed together than for individual pixels or land parcels treated alone; biased errors never decrease with averaging, whereas random errors disappear. Thus even though the analysis above suggests changes at an individual pixel-level should not necessarily be trusted unless their magnitude is relatively large (>3.1 Mg C ha^{-1}), when averaging all parcels we should expect the mean value of change to be relatively accurate (i.e. to have an extremely small uncertainty). Though this is hard to quantify in practice (one would need a large number of very large sample plots), if the variance in X is treated as a simple stochastic random variable then we would expect the error estimate to decrease by a factor of $1/\sqrt{n}$. In other words the accuracy should improve by 10-fold with a 100-fold increase in sample points (Caflish, 1998). If this last assumption is accepted then the uncertainty associated with the average change estimate for the agroforestry, degradation and REDD areas could be ±0.14, 0.64 and 0.03 Mg C ha^{-1} respectively, although because some errors associated with change are not randomly distributed in space, these smaller uncertainty values are probably unrealistic.

Finally, there is one potential source of obvious bias that could result in an underestimation of AGB loss from degradation/deforestation in this environment. After trees have been cut significant resprouting and coppicing occurs (Ryan, 2009), and it is possible that this change in structure will result in higher radar backscatter than its biomass would cause if it was a less disturbed forest. Our data do not allow us to quantify this effect, but it warrants further investigation.

To conclude this section:

(1) A conservative estimate of the accuracy of the change detection values can be derived from the RMSE values for 2007 and 2009, assuming errors are uncorrelated, giving a figure of ±9 Mg C ha^{-1}.

(2) A less conservative estimate can be derived from the RMSE of the difference in AGB estimates for the field plots: this is ±3.1 Mg C ha^{-1}.

(3) The above two estimates are derived at the plot level, using an average plot size of 0.64 ha; if the errors are randomly distributed, then the uncertainty values above should fall by a factor of 10 for every 100-fold increase in the area assessed.

Accuracy of detected increases in AGB

If the uncertainty values predicted by (3) above are accepted, then this leaves the question as to why the REDD areas appear to have increased in AGB considerably faster than the agroforestry areas (2.2 ±0.14 Mg C ha^{-1} vs. 0.74 ±0.03 Mg C ha^{-1} over the 2-year period). It is possible that this is genuinely occurring on the ground: though rapid, it is not ecologically unfeasible for the REDD areas to have increased this fast; but for the agroforestry areas new young trees do not increase in biomass rapidly for the first few years, so the increases should be smaller. Regrowing Miombo woodland in this area has been observed to increase by 0.5-1.0 Mg C ha^{-1} $year^{-1}$ (Williams et al. 2008), so an increase of 1.11 Mg C ha^{-1} yr^{-1} observed in the REDD areas is comparable to field data (it should be noted that under the alternative methodology this increase is +0.9 Mg C ha^{-1} yr^{-1}, within the range observed in the field data (Appendix A)). However this rate is definitely higher than would be expected for relatively mature Miombo woodland. As regards the relatively low value for the agroforestry plots, it is possible that changes in the structure of the agroforestry areas (for example clearing shrubs) could be reducing the perceived increase in backscatter, resulting in an underestimate of biomass increase in these areas. Once again, this can only be assessed by further investigation, involving biomass assessments on plots in these different areas. However, both these changes have a small magnitude and large range (Figure 4), and given the short detection period and errors and uncertainties inherent in this methodology perhaps the only conclusion that can be made is that both agroforestry and REDD areas are on average maintaining or slightly increasing their biomass.

Comparisons and combinations

The radar data we present here has been much more useful to the project management team than attempts to monitor changes in AGB in the site using optical remote sensing data (L. Goodman, pers. comm.). The detection of degradation (in addition to true deforestation) is very useful, as will be the assessments as to which areas are gaining AGB fastest. Ignoring the issue of cloud cover, optical data cannot detect changes in biomass directly in these ecosystems; instead it can only be used to detect step changes in the vegetation type. Even then, differences in the time of year of the imagery can confound the analyses, as the tree and grass layers gain and lose vegetation at different times. However, by giving information on landcover, optical data can contribute to the interpretation of the radar data, for example by allowing management to determine whether substantial degradation or deforestation is occurring in a particular landcover type, or to recommend the use of different AGB-backscatter equations in different forest structures.

Landcover information may also be important, because only AGB is measured by the radar method presented here, but reporting of stocks and changes in all five carbon pools (AGB, below-ground biomass, dead wood, litter and soil organic matter) are required by the UN process (as defined in IPCC, 2003). The values of these other pools are often positively correlated with AGB, but careful field studies and landcover mapping may be necessary to allow their value to be scaled to the landscape level, and for the total emissions from deforestation or degradation to be estimated (GOFC-GOLD, 2009).

Ultimately airborne LiDAR appears to be the most accurate remote-sensing tool for tracking changes in AGB. By giving a three-dimensional picture of a forest at a very high resolution, even small changes can be detected, with no saturation point (Clark et al. 2004). However, though large-scale LiDAR analyses are becoming more feasible (Asner et al. 2010), it still remains very expensive, beyond the budget of the vast majority of carbon forestry projects, and also very time-consuming over large areas. Radar satellite data represents a good alternative, especially for measuring changes in above-ground carbon stocks at a regional to national scale with relative ease.

At a far lower cost to the user than airborne LiDAR is spaceborne LiDAR data, which can be used to estimate canopy height and other structural characteristics that are closely correlated with AGB (Saatchi et al. 2011; Mitchard et al. 2011b). However, there are currently no spaceborne LiDAR systems in operation, and the launch dates for new satellites will not be before 2016 (ICESat-2). Even then such satellites will not replace radar data, as unlike aircraft-borne LiDAR they will only sample the landsurface footprints on the order of 20 m in diameter, rather than centimetres, as in aircraft-borne LiDAR. Instead, spaceborne LiDAR will be used as a tool for calibrating and extrapolating the other remote sensing methodologies.

One concern about the use of L-band radar data is the current lack of any satellite currently collecting such data: ALOS PALSAR operated from January 2007 – April 2011, but will not be replaced by ALOS-2 until 2013. There are at least two potential missions that could provide data continuity beyond the ALOS program, with potential launch dates towards the end of this decade: NASA's DESDynI mission (L-band) and ESA's BIOMASS mission (P-band), but the status of neither satellite is confirmed.

5. Conclusions

We have shown that satellite radar data can be used to measure changes in AGB in a Miombo woodland agroforestry and avoided deforestation project. Degraded areas showed a marked decrease in estimated carbon stocks, whereas agroforestry and REDD areas showed a small increase. Our field data did not include estimates from the ground as to the magnitude of changes within these areas, so further work is needed to estimate accuracies of the change detection results. However, these results suggest that a series of annual radar mosaics has the potential to be a very useful monitoring tool for carbon forestry projects.

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Author Contributions

The study was contrived by EM, PM, MW and CR. The field data were collected and analysed by CR, EW, LG, JM and MW. EM processed the remote sensing data, performed the analyses and wrote the first draft of the paper. PW and EM performed the review of CCBA REDD projects' methodologies. All authors contributed to refining the analysis and producing the final draft of the paper.

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Financial Declaration

Envirotrade has a financial interest in the success of the Gorongosa Community Carbon Project, and LG, JM and PW are employees of Envirotrade. This has not influenced the analysis nor the findings presented. EM, PM, CR, EW, MW, IW and SS have no financial interests in the project, and are independently funded as research scientists by their respective institutions.

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Tables

Table 1 – Baseline calculations used by approved Climate, Community and Biodiversity Alliance (CCBA) REDD projects

Project Name	Location	Land use change driver	Baseline deforestation rate calculation method	Source
Kasigau Corridor, Phase 1	Rukinga Sanctuary, SE Kenya	Slash and burn by subsistence farmer population.	Landsat 5 data from 1995 and 1999, manually interpreted, no ground truth data or more recent imagery. Modelling based on fixed rate of deforestation per person per year.	http://www.climate-standards.org/projects/files/taita_taveta_kenya/Rukinga_CCB_PDD_Ver_2_0.pdf
Madre de Dios Amazon REDD Project	Acre River Basin, Madre de Dios, Peru	Illegal logging and slash and burn agriculture by local people and migrants.	Classification of Landsat 5 & 7 images from five time points from 1990 – 2008. Baseline modelled using the spatially explicit model by DINAMICA EGO.	http://www.climate-standards.org/projects/files/madre_peru/Madre_de_Dios_Amazon_REDD_Project_REVISED.pdf
Reducing carbon emissions by protecting a native forest in Tasmania	Northern Midlands Region, Tasmania, Australia	Logging concessions.	One Landsat 5 scene (2006) used to build an aboveground biomass map, using a weak relationship between a vegetation index and biomass. Baseline modelled using the spatially explicit model in the FULCAM software package.	http://www.climate-standards.org/projects/files/tasmania/REDD_Forests_CCB_PDD_FINAL_071609.pdf
Avoided Deforestation in the Coffee Forest of El Salvador	Western, Central and Eastern Regions of El Salvador	Coffee farmers cutting down trees due to falling coffee prices.	Calculated solely from probability that specific coffee farmers will go under in a specific year, with the prediction that their trees will be cut down if they cannot earn a living from coffee.	http://www.climate-standards.org/projects/files/pdd_para_sgs/ficafe_PDD_v06.pdf
The Rimba Raya Biodiversity Reserve REDD Project	Kalimantan (Borneo), Indonesia	Conversion to palm oil.	Classification of 6 Landsat scenes from 2000 – 2008 gives a baseline rate of conversion from forest to palm oil. Uses a simple, non-spatially-explicit model to extrapolate current conversion rates into the future.	http://www.climate-standards.org/projects/files/rimba_raya/CCBA_PDD_Submission_for_Public_Comments_2010_06_05.pdf
The Juma Sustainable Development Reserve Project	Amazonas State, Brazil	Agriculture and cattle grazing.	Uses a sophisticated SimAmazonia 1 spatially explicit model, incorporating INPE PRODES satellite-derived deforestation maps and an extensive set of social and GIS layers to predict future deforestation rates.	http://www.climate-standards.org/projects/files/juma/PDD_Juma_Reserve_RED_Project_v5_0.pdf
Reducing Carbon Emissions from Deforestation in the Ulu Masen Ecosystem	Aceh Province, Sumatra, Indonesia	Agriculture and logging.	Deforestation estimated at 0.86 % per year, and linearly continued into the future, based on an unpublished Conservation International report. Current carbon stocks estimated using default values for disturbed and undisturbed forest, with these two classes differentiated using SPOT satellite imagery from 2006.	http://www.climate-standards.org/projects/files/cambodia/CCB_PDD_Oddar_Meanchey_NORMAL_RES.pdf

Table 2 - Details of ALOS PALSAR scenes used in the analysis

Scene ID	Date	Centre coordinate
ALPSRP075236800	10 July 2007	34.367 E, 18.899 S
ALPSRP077716800	23 June 2007	33.832 E, 18.900 S
ALPSRP196016800	28 September 2009	34.367 E, 18.899 S
ALPSRP185076800	15 July 2009	33.832 E, 18.900 S

Table 3 – AGB change derived from radar data for landcover parcels with different landcover trajectories

Landcover	Mean AGB 2007 (Mg C ha^{-1})	Mean AGB 2009 (Mg C ha^{-1})	ÀGB Change (Mg C ha^{-1})	Total area (ha)	Number parcels	Average size of parcels (ha)
Agroforestry	15.22	15.96	**+0.74**	500.45	546	0.92
Degradation	29.35	23.26	**-6.09**	23.26	6	3.88
REDD	26.38	28.60	**+2.22**	9504.06	38	250.11

Figures

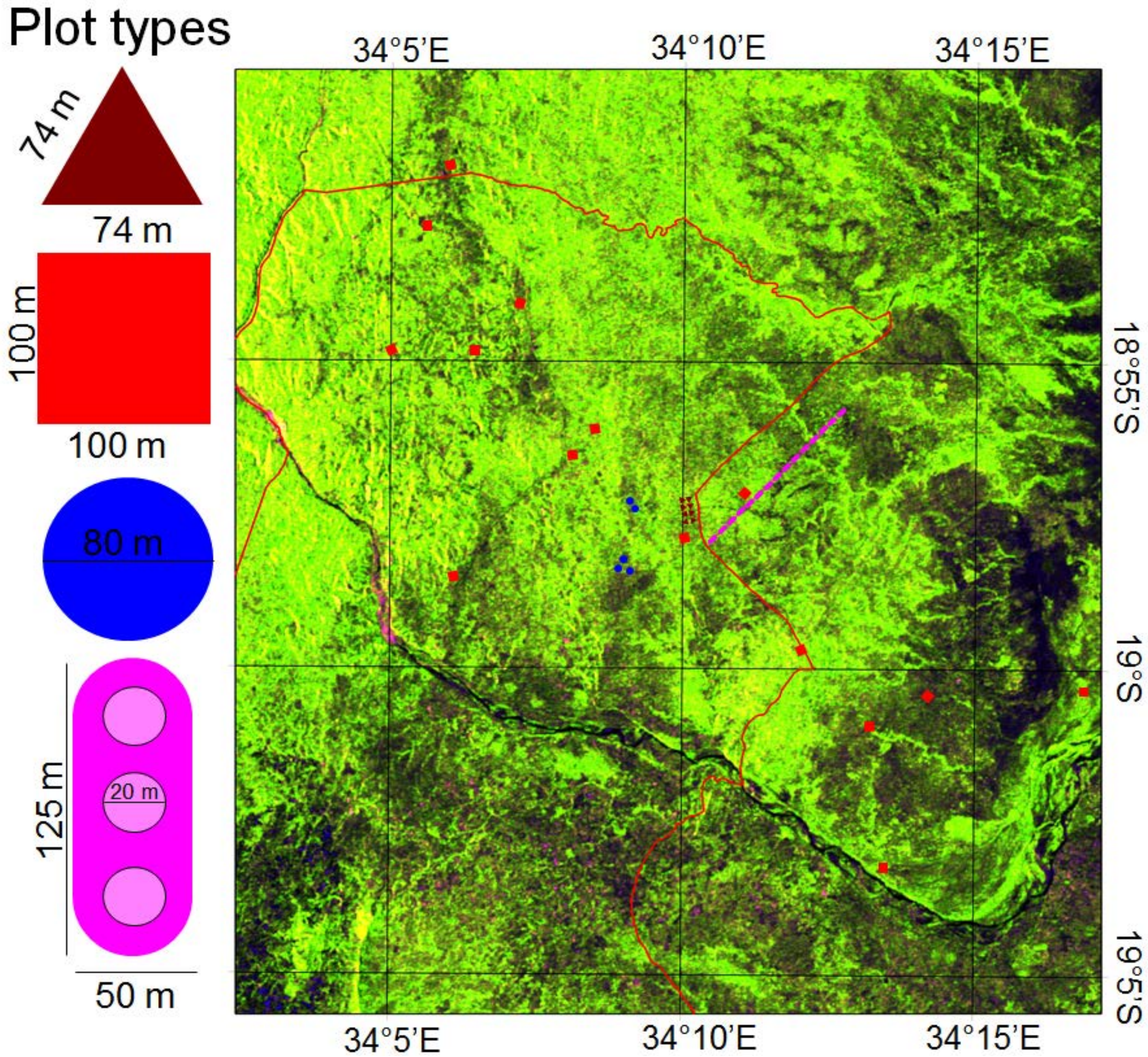

Figure 1: Map showing the location of the AGB field plots used in this study. The field plots are shown with every dimension doubled (area quadrupled) compared to reality. Due to this scaling it was only possible to show 15 of the 30 ellipse-shaped plots: in reality there are two plots under every one shown. The background image is the ALOS PALSAR radar-mosaic from 2007, at 25 m resolution, with the red, green and blue bands being HH, HV, and HH/HV respectively. Bright green and yellow correspond to the most forested areas, with darker colours being low-biomass shrub and croplands. The boundary of the Gorongosa Community Carbon Project is shown in red.

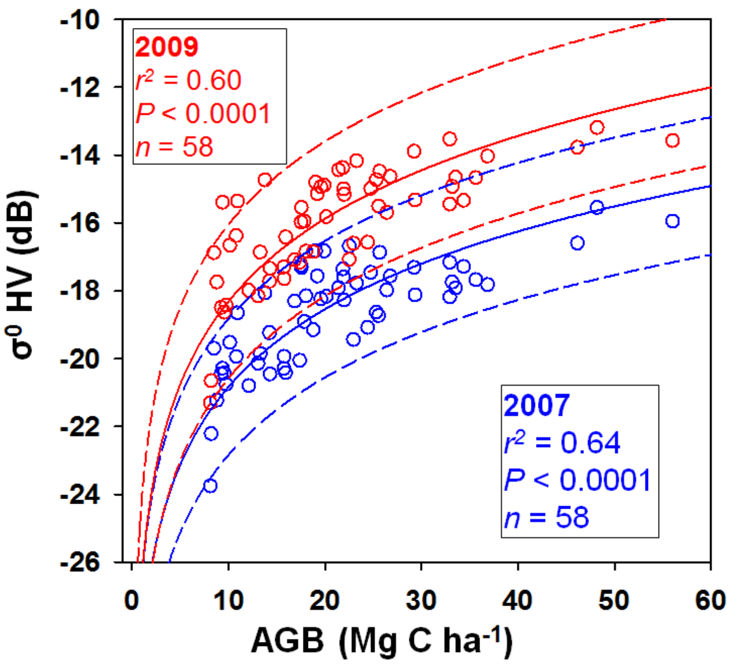

Figure 2: HV radar backscatter plotted against aboveground biomass (AGB, Mg C ha^{-1}), for 2007 (blue) and 2009 (red). The field plot AGB values are assumed to be identical at both time points. The solid lines are RMA regressions of radar backscatter ($sigma^0$) with log AGB, the dotted lines show the prediction intervals for the regressions.

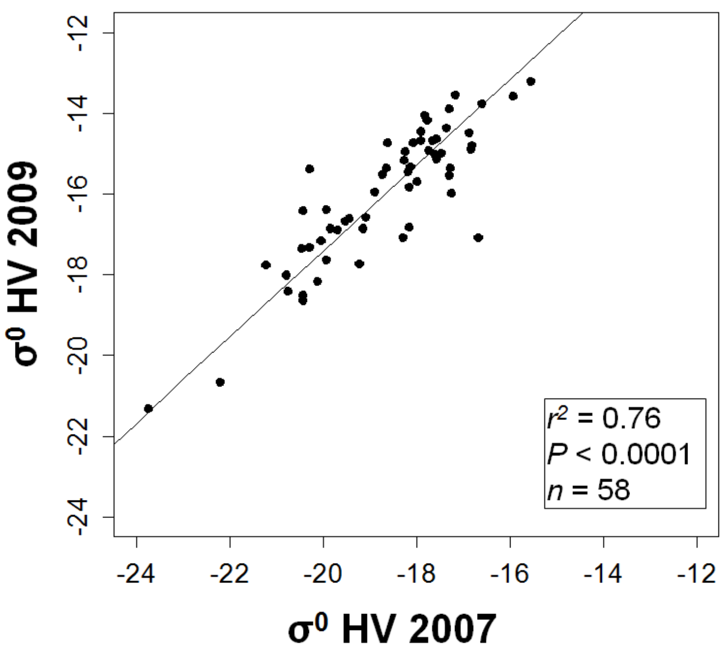

Figure 3: HV backscatter for the 58 AGB plots from 2009 plotted against the HV backscatter in 2007. A linear RMA regression line is fitted.

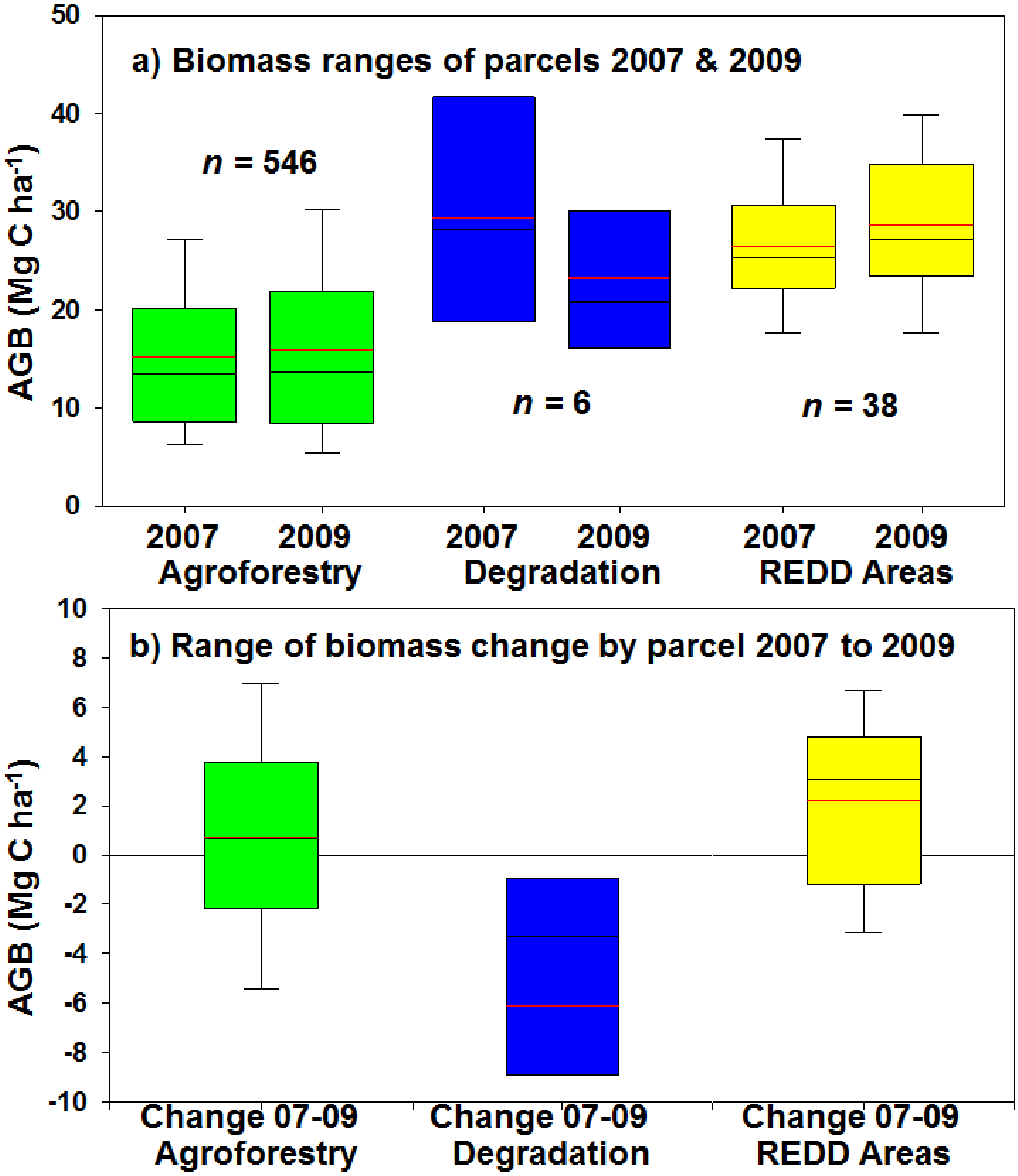

Figure 4: Box and whisker plots showing the (a) distribution of AGB values for parcels of land in the three treatment types in 2007 and 2009, and (b) the changes in AGB for each parcel from 2007 to 2009, in both cases derived from HV radar data. The black line in the middle of each box gives the median value of each dataset, the red line the mean; each box represents the spread of the middle 50% of the data (between the 25th and 75th quartiles); the whiskers give the 10th and 90th quartiles. For the deforested areas there are only 6 plots, so the 10th and 90th quartiles cannot be calculated, and thus only the box is shown.