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A method and case study from central Mozambique

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Quantifying the causes of deforestation and degradation and creating transparent REDD+ baselines: a method and case study from central Mozambique

Abstract

Reductions in deforestation and forest degradation are advocated as a means to mitigate climate change. The formulation and implementation of policies to achieve such reductions requires an understanding of current and historic land-use change and associated greenhouse gas emissions. In addition, it is often proposed that any reduction in emissions be measured against a reference scenario that describes future land-use in the absence of intervention. However, the information needed to progress this agenda is rarely available, as robust data on the extent and causes of land-use change, and the associated changes in carbon stocks, are sparse, particularly in African woodlands. Here we present a novel method for obtaining such information by combining data from radar remote sensing and ground surveys with a simple aspatial model. Using this approach we quantify changes in woody biomass and investigate the land-use activities that caused these changes in a 7500 km^2 area of Manica province, Mozambique. We use the data to construct a model linking the activities causing biomass loss to hypothesised drivers, allowing the definition of future scenarios. Within the study area, biomass was lost at a rate of 2.8±1.9% per year, from 19.4±0.9 TgC in 2007 to 17.6±0.9 TgC in 2010. Small-scale agriculture was the direct cause of 46±17% of the total biomass loss, followed in magnitude by construction and miscellaneous activities (24±11%), charcoal production (18±9%), logging (9±5%) and commercial agriculture (3±2%). Uncertainties remain on the biomass accumulated by regrowing vegetation. Extrapolating into the future, a scenario that includes projected population growth shows 41% of biomass being lost from 2010-2020 (a loss of 7.2 TgC). A scenario of intensive policy interventions gives reduced losses of

3.8 TgC by factoring in improvements in crop yields, charcoal production efficiency, and sustainable timber harvesting. Our case study demonstrates the importance of low intensity losses of biomass in African woodlands, and highlights the broad range of activities that will need to be addressed to develop locally appropriate mitigation actions. The simple modelling framework allows for the transparent creation of scenarios in data sparse areas, which could be used as local or national reference emissions levels under REDD+.

1. Introduction

Reducing deforestation and forest degradation in developing countries has received considerable political attention over the last decade. The idea has broadened markedly since discussions began in 2005, but the basic idea of incentivising reduced emissions from a variety of land uses remains. This provides several challenges for land change science: Firstly, the development of policy and interventions that effectively reduce deforestation and forest degradation requires an understanding of the historical rates and drivers of land-use change. Secondly, if such actions are to be supported by performance-based finance opportunities, counter-factual reference scenarios of land-use change against which progress can be assessed are likely to be required (Griscom et al., 2009). Meeting these information needs is hindered by sparse data on the causes of deforestation and degradation (Agarwal et al., 2005), and the difficulties of estimating the rates of the latter (Herold et al., 2011).

Conversion of forest to croplands is thought to be the single largest cause of land-use change emissions globally (Houghton, 2010; Houghton, 2012; DeFries et al., 2010), but site-specific information is generally lacking and remote sensing analyses are not usually able to describe changes associated with small-scale farming activities and shifting cultivation. In its absence, local information is generally inferred from a small number of case studies (e.g. 19 cases studies in Africa by Geist & Lambin (2002)), or based on estimations and expert judgement (Blaser & Robledo, 2007). More recently, national governments have identified the drivers of forest loss at a national scale (summarised in Kissinger et al., 2012). However this process shows that in most countries there is little evidence to support current assumptions about the nature and importance of both proximate causes and underlying drivers of deforestation and degradation. In countries where wood harvesting for timber or energy supply is extensive, or shifting cultivation widespread, which includes a large part of the developing world (Silva et al., 2011), narratives of the causes of deforestation and degradation have generally developed without a strong evidence base (e.g. Hansfort & Mertz, 2011; Ickowitz, 2006; Laris & Wardell, 2006; Ribot, 1999; Angelsen, 1995).

Given the uncertainty of current estimates of greenhouse gas emissions from land use, and the lack of understanding of drivers of land-use change, it is not surprising that the UNFCCC is yet to provide specific guidance on the approaches countries should take to setting reference levels against which REDD+ performance can be assessed. Two points on which consensus has been reached are that reference levels must *"transparently tak[e] into account historic data"* and that they can be adjusted to "*national circumstances"* (UNFCCC, 2009, p. 12). Options for setting reference levels for REDD+ therefore include: i) A strictly historical approach that only considers average rates of land-use change during the recent past; ii) An adjusted historical approach that takes account of national circumstances such as the likelihood that deforestation will increase in the future; and iii) Simulation models that statistically link country specific information on deforestation drivers to patterns of land-use change (Herold et al., 2012).

The incorporation of national circumstances into reference levels allows more realistic assessment of the benefits of REDD+ than simple extrapolation of historic patterns, but there are currently no guidelines on how this should be done. The absence of guidance on this issue introduces the potential for distortions that make the impacts of REDD+ activities seem more favourable, if those carrying out REDD+ activities are left to decide which environmental and socio-economic aspects to take account of and how they should be treated. To develop plausible and credible REDD+ reference levels, which take account of national circumstances, therefore requires an understanding of historical land-use changes and their causes, and transparent approaches for using this information to model future scenarios of change.

Recent developments in radar remote sensing have enhanced our ability to quantify land-cover change (LCC) in the tropics (Hoekman et al., 2010; Rahman & Sumantyo, 2010). Given appropriate wavelengths, the normalised radar cross section, or backscatter, correlates with aboveground woody biomass for densities typical of woodlands (Le Toan et al., 1992; Rignot et al., 1994; Lucas et al., 2010). The collection of such data is largely unaffected by clouds and smoke, reducing atmospheric effects and facilitating change detection (Magnusson et al., 2007; Karjalainen

et al., 2009; Mitchard et al., 2011). Recent work has shown that in the African woodlands, time series of radar data can be used to estimate both deforestation and degradation at a resolution of 25 m, high enough to capture most LCC events (Ryan et al., 2012). However, such techniques have not yet been applied to quantify the extent of the activities that cause forest loss.

The aim of this paper is to combine radar remote sensing and targeted ground observations to estimate LCC and the associated changes in carbon stored in above ground woody biomass (hereafter termed biomass), and apportion biomass change to various land-use activities (LUAs). To demonstrate the application of these data to the issue of creating reference levels, we construct a simple model to link the activities causing deforestation and degradation to underlying drivers, and construct future scenarios to determine the scope for emission reductions.

2. Methods

We make the conventional (Lambin et al., 2006) distinction between i) changes to the biophysical land surface (termed land-cover change, LCC), which are quantified using radar remote sensing, and ii) human activities that cause these changes (land-use change activities, LUAs), which are quantified with on-the-ground observations and interviews. To construct future scenarios of biomass change, we make a further distinction between the proximate *causes* of LCC, observed as LUAs, and the underlying *drivers* of change. Our methods are thus separated into four parts: i) the use of radar imagery to map changes in biomass; ii) ground observations of LUAs and associated up-scaling; iii) the construction of a simple cause-driver model and its application to reference and intervention scenarios; and iv) analysis of uncertainty in our estimates.

2.1. Site description

The study area covers 7500 km^2 of Gondola and Sussendenga districts in Manica Province, central Mozambique, south of the city of Chimoio (Fig.1). Manica Province had a population of 1.44 million in 2007, projected to rise to 2.29 million in 2020, a per capita annual increase of 3.57%

yr^{-1} (INE, 2012). Livelihoods in rural areas are based primarily on small-scale agriculture, with farm sizes of 1.74±0.51 ha (with mean ± standard deviation) per household and maize as the dominant crop (Thurlow, 2008). Large-scale commercial agriculture is expanding in the area, involving both biofuels (Schut et al., 2010; AgriIQ, 2010) and fruit crops (NJ personal observation, 2011). The region has a seasonal wet-dry climate with ~1090 mm rain yr^{-1} (INAM, 2011) and is dominated by miombo woodlands in the gently undulating plains, with higher biomass dry forest on the slopes of the Chimanimani Mountains.

≪fig 1 here≫

Fig. 1. Location of the study site in Mozambique, overlaid on a digital elevation map (source: Shuttle Radar Topography Mission; Farr et al., 2007). Also shown is the study area of Ryan et al. (2012), from where the biomasss-backscatter relationship was obtained.

2.2. Land-cover change: Multi temporal remote sensing observations of biomass

Carbon stored in aboveground woody biomass (tC/ha) in the study area was estimated from images obtained by the Phased Array L-band Synthetic Aperture Radar sensor on the Advanced Land Observing Satellite (ALOS PALSAR) in the Fine-Beam Dual mode, horizontal-send vertical-receive (HV) polarisation (Shimada el al., 2010). Fourteen images, acquired from May-September (the dry season months) of 2007 - 2010 were processed by mosaicking two scenes, converting digital numbers to backscatter using the calibration coefficients of Shimada et al. (2009), applying a geometric and radiometric terrain correction using the Alaska Satellite Facility's MapReady software v2.3.6 (ASF, 2010) and 90 m SRTM elevation data (Shuttle Radar Topography Mission; Farr et al., 2007), and resampling from 12.5 m to 25 m resolution (see Ryan et al. (2012) for full details of this method). To estimate biomass from backscatter, the equation of Ryan et al. (2012) was used, assuming that the backscatter-biomass relationship estimated in their study area (200 km away) is valid in the present study. The vegetation in the two study areas is similar, being dominated by miombo woodland (Fig 1) and the acquisition months of the radar data are the same. To produce accurate change detection statistics and to account for inter-annual variability in soil moisture and other changes to backscatter unrelated to biomass, we first averaged all images from

each year's dry season (2 each for 2007, 2009 and 2010; 1 for 2008) and then normalised each yearly composite to 2010 using 89 pseudo invariant objects (PIOs) - areas thought not to have undergone land-cover change. PIOs ranged in size from 5 to 3029 ha and were selected across a range of backscatter values varying from open fields to remote forest (range in mean backscatter -25.2 to -10.7 dB). Differences between each year's backscatter were corrected using linear regression (all $R^2 > 0.99$) following the (radar-relevant) guidelines of Heo & FitzHugh (2000).

To quantify the causes of land-cover change in the study area, we delineated distinct LCC "events" that could be investigated on the ground. These events were delineated based on thresholds of biomass change between 2007 and 2010, by grouping adjacent pixels that underwent change of similar intensity (I). Intensity is defined as $I = B_{2010}/B_{2007}$, where B_{2007} and B_{2010} indicate the estimated biomass area-density (tC/ha) of the pixel in each year. To simplify the analysis we use a binary classification of I: high where $0 \leq I \leq 0.5$ and low where $0.5 < I \leq 0.8$. To avoid noisy data resulting in false positives, only contiguous areas > 3 pixels (>0.1875 ha) were included. Ignoring areas smaller than this and those where $I > 0.8$, excludes some areas of small low-intensity loss, meaning that the LCC events are a subset of total C loss in the area. It does however reduce the occurrence of false positives (Ryan et al., 2012). Areas with $B_{2007} < 10$ MgC/ha are not included as a part of the study area, as biomass estimates at low levels are subject to additional error (Ryan et al., 2012).

To facilitate stratified sampling, and avoid sampling bias caused by differential accessibility, all LCC events were classified according to the intensity of biomass loss, distance from roads ('close' ≤ 4 km or 'far' > 4 km) and area ('small' 0.1875 to 1 ha or 'large' >1 ha), resulting in 8 LCC categories. A random subsample of 400 events was identified, transferred to GPS and 76 of the subsample were visited in October 2011. The 76 events were selected for logistical reasons, and included all eight LCC event categories. "Far" events were much more time consuming to visit and 29 were visited in total.

2.3. Land-use activities: ground observations

LCC events were visited in Oct 2011 to determine the LUAs that had caused the change in land-cover between 2007 and 2010. The causes of past change were established by triangulating information from local land managers and field guides, as well as observations of the type of clearance and any residual features of the LUAs. In addition to the randomly selected sample, all LCC events resulting from commercial agriculture in the study area (3 in total) were visited.

To estimate the biomass loss (ΔB) associated with each of the j LUAs, where j = {small scale agriculture, construction activities, charcoal production and logging}, we use equation 1:

$$\Delta B_j = \sum_{i=1}^{8} \frac{n_{i,j}}{n_i} \Delta B_i \qquad \text{(Eq. 1)}$$

Where: $n_{i,j}$ is the number of LCC events observed in the i-th LCC category, caused by the j-th LUA, and n_i is the total number of LCC events of category i. ΔB_i is the sum of biomass changes in all LCC events in the i-th LCC category.

As such, the sum of biomass losses for all LCC events in each category was attributed to each LUA in proportion to the number of observations of each LUA in that LCC event category. Where >1 LUA was identified as the cause of a single LCC event, we estimated the contribution of each LUA (by area) and assigned biomass losses pro rata. Events where no LUA could be identified (termed 'unknowns') were assumed to be either false positives, or caused by activities such as fire, elephants or natural forest dynamics. Since all (large-scale) commercial agriculture LCC events were identified in the study area, biomass loss for this activity was calculated directly from the biomass map. There is one further complication to address before a sample of LCC events can be used to scale up to the study area. This arises because the discrete LCC events include only a subset of the net biomass change across the whole study area (ΔB), since small areas and those with low intensity changes are excluded by definition, as were areas of biomass increase. To address this we simply scale the change in biomass associated with each activity (ΔB_j), such that total losses associated with each activity sum to the total net change observed across the study area.

Commercial agriculture was not included in the scaling, since all events were sampled and no associated biomass increases were observed.

2.4. Scenarios of future biomass change

To illustrate the uses of the information generated by our analysis, we construct two scenarios of change in biomass from 2010-20: a 'reference scenario' describing expected change if current relationships and trends continue, and an 'intervention scenario' describing the impact of several changes to current practices. Both scenarios depend on a simple cause-driver model that utilises a hypothesised link between the observed biomass loss caused by each activity (the proximate causes: small-scale agriculture, charcoal production, logging and construction) and the magnitude of the underlying drivers. This linkage can be represented as:

$$\frac{\Delta B_j}{\Delta D_{2007-10}} = k_j \frac{\Delta B_{j,2010-20}}{\Delta D_{2010-20}} \qquad \text{(Eq. 2)}$$

Where ΔB_j is the losses caused by activity j in 2007-10 from Eq. 1, and $\Delta D_{2007-10}$ is the recorded change in the level of the driver in 2007-10 (Table 1). The projected changes in the level of each driver (Table 1), and resultant estimated change in biomass losses, is shown with the subscript $_{2010\text{-}20}$. k is defined as unity for the reference scenario, but is varied for each activity under the intervention scenario. In our example (Table 1) small-scale agriculture is assumed to be driven by changes in total population in the study area. This assumption is due to the ubiquity of subsistence agriculture as the main livelihood in rural areas (Jansen et al., 2008) and the reliance of urban and semi-urban areas on locally produced food. Charcoal production is assumed to be driven by increasing urban population in nearby cities, as charcoal is the primary and preferred domestic energy source in urban areas (Cuvilas, 2010) and rural consumption is rare. Although per capita consumption is likely to change with changing prosperity, this is not accounted for in the model. Construction activities were linked to rural population change, since most observed events were associated with the construction of new rural dwellings or schools. Finally, the extent of

commercial logging was linked to international timber export volumes due to the lack of localized information on domestic demand.

Table 1. Causes and assumed drivers of biomass loss in the scenarios.

Activity causing biomass change	*Assumed underlying driver*	*Data source for driver (2007-10)*	*Data source and basis for projection of driver (2010-2020)*	*High/Low variants of driver*
Small-scale agriculture	Change in total study area population.	INE (2012)	District-level population projections from INE (2012)	Population growth increases/ decreases such that the population in 2020 is ±2% of the INE projection (consistent with variants in UNPD (2012)).
Logging	Total international wood export volumes from Mozambique	Global Timber (2011) & Canby (2008)	Extrapolation of historic observations with a 2nd degree polynomial	Changes in export volumes increase/ decrease such that volumes in 2020 are ±50% compared to the extrapolation of current trends.
Charcoal	Change in urban population of Sofala and Manica.	INE (2012)	INE (2012)	As per small-scale agriculture
Construction	Change in rural population.	INE (2012)	INE (2012)	As per small-scale agriculture
Commercial agriculture	Expansion plans and recently granted land concessions were used to estimate future losses	n/a	Nhantumbo &Salomão, 2010; AgriIQ, 2010; Local employee and residents' knowledge.	Area of land used is increased/ reduced such that C losses in 2020 are ±50% as compared to reported plans.

To investigate the scope for changes in current land use practices (hereafter interventions) to alter the cause-driver linkage and reduce modelled biomass loss, the intervention scenario models improvements in crop yields, charcoal production efficiency and logging practices. For simplicity, no interventions were modelled to construction activities. Practical examples of these three interventions are relatively numerous and the intervention scenario is thus constructed based on data from documented examples of interventions in similar land use systems (Table 2). In all cases we assume that intensification of production leads to less forest clearance, something that is not always observed (Angelsen, 2010) and which requires careful policy design. In both scenarios, the expansion of commercial commercial agriculture was considered differently from other causes and instead of being linked

to a driver, was estimated by considering known plans for expansion by companies operating in the area, obtained by interviews and from government sources.

Table 2. The basis for modification of the cause-driver linkage in the intervention scenario.

Land-use activity	*Basis of intervention and modification of the cause-driver linkage*	*Modelled impact of intervention and justification*
Small-scale agriculture	Increased yields of staple crops might reduce the new area needed for cultivation. For simplicity only maize yields are considered as they account for 50% of cultivated area (Thurlow, 2008). All other aspects of the current food system are assumed constant, including food consumption rates, farm size, non-agriculture workforce employment etc.	Maize yields are increased 2.8 fold by 2020, from 0.9 t/ha in 2005 (World Bank, 2006). A 2.8-fold increase is comparable to the level achieved in one year in the African Millennium Villages (Sanchez et al., 2007).
Logging	Timber harvesting techniques can be modified to cause no net loss of forest biomass over a rotation i.e. by only harvesting an annual allowable cut. This is currently required of forest concession holders in their management plans, but not of 'simple license' holders' (Nhancale et al., 2009).	Production moves from 'simple licence' to a forest concession arrangement, where harvesting is largely undertaken within the annual allowable cut (in accordance with current government plans (Nhancale et al., 2009; Sitoe et al., 2003)). Each year 5% of log production was assumed to move to a no net loss system.
Charcoal	Charcoal kiln production efficiency is modified such that more charcoal can be produced for a given input.	Production efficiencies are increased from 17.5%, the average found in Mozambique (Pereira, 2001), to 30%, based on achievable efficiencies of improved Earth Mound Kilns and Brick Kilns (Malimbwi, 2000; Seidel, 2008; Falcão, 2008)

2.5. Error analysis

Error estimates were generated for the estimates of land-cover change and changes in biomass associated with each LUA. The major sources of uncertainty were identified as i) potential bias in radar-derived estimates of biomass at each time point, which lead to error on estimates of loss rates, ii) sampling error associated with the subsample of LCC events visited. The error associated with i) has been quantified in Ryan et al. (2012), and their estimate of 1 SE of the bias of 1.6 MgC/ha was adopted. The uncertainty on each year's observation is considered independent of subsequent years, a conservative assumption (Ryan et al., 2012). Errors for change statistics were calculated using the standard error propagation formulae. Error on the biomass loss rate was derived from the curve fitting procedure, and based on the standard error of the slope parameter. Errors associated with ii) were quantified using the formula for the standard error of a proportion, and this

was combined with the errors associated with biomass change, assuming the variables are uncorrelated.

3. Results

3.1. Land-cover change

The biomass maps show a strong variation in biomass associated with proximity to the city of Chimoio and an east to west gradient associated with the topography. A halo of low biomass surrounds the city of Chimoio and a 'wave' of forest loss and regrowth circles the city.

Fig. 2. Biomass change intensity ($I = B_{2010}/B_{2007}$, where B_{2007} and B_{2010} indicate the estimated biomass area-density (tC/ha) of the pixel in each year) in the study area. 200% (green) indicates a doubling of biomass between 2007 and 2010; 100% (grey) indicates no change and 0% (black) indicates total loss of biomass. Roads are marked as black lines, and include the EN1 highway to Maputo and the EN6 highway (to Beira/Mutare). Rivers are marked in blue. Areas with biomass < 10 MgC/ha in 2007 are not included in the study and are shown in white. Lettered areas A-E are referred to in text and numbered boxes 1-3 are locations of the examples LCC events described in Fig. 3.

≪fig 2 here≫

Fig. 3. Examples of land-cover change. Leftmost images show the biomass ratio (*I*) with the same colour scale as Fig. 2. The yellow polygon marks the discrete LCC event delineated by thresholding *I,* and the black bar indicates 500 m scale. The centre images show true colour optical imagery from the Worldview satellite (2 m resolution; image acquisition date: July 2011). The rightmost images show photos taken during fieldwork in October 2011. 1) Shows an area cleared for small-scale agriculture, 2) an area of charcoal production, and 3) large scale agriculture (mango plantation).

≪fig 3 here≫

Estimated biomass in the study area decreased from 19.4±0.9 TgC in 2007 to 17.6±0.9 TgC in 2010 (Fig. 7), equivalent to a mean C area density of 36 MgC/ha in 2007 and 33 MgC/ha in 2010. Net change in biomass, estimated from a linear fit to the 2007-10 data was estimated at -8.3±5.7% of the 2007 biomass, equivalent to -533±362 GgC/yr (-2.8±1.9 %/yr). This net change was composed of gross losses of 3.4±2.3 TgC and gross gains of 1.8±1.2 TgC over 3 years. Areas delineated as LCC events account for 74% of gross losses in the study area. High intensity loss events were less numerous, slightly larger in area, and accounted for roughly the same amount of biomass loss as low intensity events (44±26% vs 56±33%).

3.2. Land-use Activities

The most commonly observed LUA was small-scale agriculture (27 of 79 observations; causing 35±5% of events across the study area) followed by construction activities, including pole harvesting and land clearance for infrastructure (~18; 23±5%), charcoal production (~11; 13±4%), unknowns (~11; 13±4%) and logging (~9; 11±4%). New informal roads near Sussendenga and Macate had facilitated much of the recent logging. Charcoal production was found in many areas within ~50 km of Chimoio, and also along the EN1. Three commercial agriculture events were identified and visited, and were found to be export-orientated commercial mango and sugarcane plantations.

≪Fig 4 here≫

Fig. 4. Distribution of observed land-use activities by land-cover change event category. High and low intensity indicate events which lost ≥50% and 20-50% of biomass, respectively. 'Large' and 'Small' indicates events > 1 ha or ≤ 1 ha. 'Close' and 'Far' indicate the proximity to mapped roads, either ≤4km or >4km, respectively.

LUAs were not uniformly distributed in the different LCC event categories (Fig. 4). The clearest linkage was between small-scale agriculture and high intensity events (~22 of the 37 intense LCC events were small-scale agriculture). Low intensity LCC events were not clearly associated with a single LUA, but were associated with all LUAs except commercial agriculture. Chi-squared tests showed that event intensity ($p < 0.001$) and distance from roads ($p = 0.03$) were unlikely to be independent of LUA, whereas event area was likely to be independent of LUA ($p = 0.71$). Small-scale agriculture was estimated to be the main cause of biomass loss in the study area (46±17% of loss). Charcoal (18±9%), logging (9±5%) and construction activities (24±11%) accounted for the remainder, but had higher error estimates due to the lower sample size. Commercial agriculture caused the lowest loss of any LUA (3±2%)

3.3. Future scenarios

Linear extrapolation of the observed biomass loss rate shows total biomass in the study area decreasing by 5.3 TgC over the period 2010-2020, from 17.6 TgC in 2010 to 12.2 TgC in 2020, equivalent to an average loss of 3.0±2.1%/yr of the 2010 biomass. At this rate, all biomass stocks in the areas would be lost by 2043. The statistical uncertainties associated with this extrapolation are however, very large, due to the small number of observations (*n*=4; Fig.7).

≪fig 5 here≫

Fig. 5 Scenarios of change in the study area. The thick line shows a linear extrapolation of the observed data (2007-10, error bars show ± 1 SD), with the 95% CI of the function shown with a dotted line. The thin solid line shows the reference scenario. The thin dashed line shows the intervention scenario. The grey shades indicate the high and low variants of the scenarios.

All the assumed drivers of biomass loss are projected to increase over the period 2010-2020. The most substantial driver, population, is projected to rise by 3.69%/yr in rural areas and 2.13%/yr in the urban areas, based on projections by INE (2012). An extrapolation of logging export volumes suggests an increase from 243,000 m^3/yr to 524,000 m^3/yr. Plans for the expansion of commercial agriculture include a 14,000 ha biofuel plantation, a 10,000 ha cattle ranching operation and the expansion of fruit plantations.

Given the increasing drivers, loss of biomass under the reference scenario is in excess of the linear extrapolation, according to the modelled cause-driver linkages. Under the reference scenario, the study area loses 7.2 TgC from 2010 to 2020, an average of 4.1%/yr of the 2010 biomass. Future losses are mostly caused by the expansion of small-scale agriculture (42%), with contributions from construction activities (23%), charcoal production (16%), commercial agriculture (10%) and logging (9%). These results however show sensitivity to projected levels of the drivers, particularly the population growth rates. High and low variants of the estimated drivers result in loss rates of 4.7 %/yr and 3.5 %/yr, respectively.

The intervention scenario results in a net loss of 3.8 Tg from 2010-20, equivalent to 2.1%/yr of the 2010 biomass, indicating that the modelled interventions only go part way in ameliorating the

increased drivers of biomass loss. The reduction in loss compared to the reference scenario (3.4 TgC) is almost entirely (89%) due to improved maize yields and the resultant modelled reduction in new land needed for agriculture. Whether improved yields will indeed result in reduced forest loss thus becomes a key area for discussion and further research.

4. Discussion

Across the study area, observed biomass loss rates from 2007-10 were high (2.8±1.9 %/yr), in comparison to previous estimates of forest area loss for Manica Province (0.75%/yr from 1990-2002, Marzoli, 2007), Mozambique (0.58%/yr from 1990-2002, Marzoli, 2007), and for the miombo region in general (national forest area loss rates range from 0.2-1.9%/yr, mean 0.8±0.6%/yr according to FAO (2011)). This is not a like for like comparison however, as previous estimates are forest *area* loss rates, and thus exclude the effects of degradation, but even accounting for a 50:50 deforestation-degradation split, these rates are probably lower than our observations. This may be because i) our study area has an atypically high loss rate compared to the rest of Manica, or ii) forest loss rates are rapidly increasing in Mozambique alongside rapid increase in GDP and population. Either way, when setting targets for reductions in forest loss, policy makers should be cognisant that commonly used estimates of forest area loss (e.g. FAO (2011) or Marzoli (2007)), may underestimate current and future biomass loss rates, and thus LUC emissions, by around a factor of 2. We note that the high loss rates found in this study are similar to those in the Ryan et al. (2012) study in Sofala, but better spatial coverage and replication of such studies is urgently needed.

This study found that high intensity loss events were primarily caused by small-scale agriculture (in line with the findings of Geist & Lambin (2002), and the estimates of Blaser & Robledo (2007)), and that low intensity losses were caused by a wide range of activities, including charcoal production and logging. Efforts to reduce deforestation and forest degradation in this area will therefore require an approach that considers agricultural development alongside forest

management. This finding reinforces the need for whole landscape approaches to REDD+ (DeFries & Rosenzweig 2010).

The two scenarios show that firstly, biomass loss under the reference scenario is likely to exceed simple historical extrapolation, and secondly, that a very substantial programme of interventions can only reduce losses, but cannot alter the trajectory of change. The intervention scenario results in a 3.4 TgC saving relative to the reference scenario. In both scenarios, increasing population, and thus small-scale agriculture, drives the majority of the increase in forest loss from 2010-2020, implying that deviations from the reference scenario will primarily be achieved by reducing the amount of land used for small-scale agriculture. Although this might be achieved by increasing yields, large (2.8-fold) gains will be needed to offset the projected rise in population. However, even if this increase is achieved, yield improvements may not lead to ‘land sparing’ (Rudel et al., 2009), and policies will need to avoid the ‘rebound effect’ (Lambin & Meyfroidt, 2011) of increased maize yields leading to larger cultivated areas (Angelsen, 2010).

The vast proportion of observed and projected losses are caused by what might be called 'unplanned' agents of biomass loss, i.e. small-scale agriculture, charcoal production and artisan logging. According to existing plans and recent observations, ‘planned’ drivers of deforestation, i.e. commercial plantations and ranching, appear to be a minor component of LUC dynamics. For example, by 2020 under the reference scenario only 5% of the land area will be used for commercial agriculture. However, current plans may be a weak guide to future activity - Mozambique has a large amount of "potentially available, good land” for cultivation (~22 Mha, Fischer & Shah, 2010; Lambin & Meyfroidt, 2011), according to global analyses, and is currently a focus of expansion for global commodity production. In particular, Manica province is being promoted as an area for expansion. This is part of a wider trend towards commercial agricultural expansion in Africa (Schut et al., 2010).

In this paper we have detailed a simple method for observing the proximate causes of forest biomass loss and scaling up to district and province level. The method requires combining field data

with assumptions about underlying drivers; but is scalable and, through a sampling approach, could provide a quantitative understanding of the rates and causes of deforestation and degradation at provincial or national level. This information is directly applicable to developing interventions to reduce deforestation and forest degradation and/or to achieve REDD+. Furthermore, quantitative understanding of the causes of deforestation and degradation provides an approach for modelling future land-use change and emission scenarios based on a transparent set of assumptions. The relative simplicity and highly transparent nature of this approach provides an alternative to spatially explicit statistical models that project the probability of land cover change occurring (e.g. GEOMOD, Pontius & Chen, 2006). Such approaches require historic land cover and social data that is often not available at a useful resolution, and also can have low predictive skill and transparency (Sloan & Pelletier, 2012). The scalable nature of our approach and the openness of the assumptions about drivers and their future magnitude make it particularly well suited to the development of REDD+ initiatives.

Three technical limitations of the methodology stand out: firstly the limited availability of radar imagery (ALOS data are available from 2007-10 at this site, although ALOS-2 should be providing data by 2015) and in situ measurements of forest carbon stocks with which to determine the biomass-backscatter relationship. Secondly, the up-scaling from a sample of LCC events to a regional estimate of biomass loss is predicated on some simplifying assumptions that warrant further investigation. These include the link between activities that cause biomass loss and those that cause biomass regrowth. This is important because, for example, regrowth after agricultural abandonment (Williams et al., 2008) needs to be set against the losses that occur during forest clearance associated with shifting cultivation to estimate the true impact of this activity. Here we assumed that regrowth occurred in proportion to forest loss, but this remains to be assessed. Finally, the biomass mapping method used here is only applicable in woodlands and not in dense forests. This is because the relationship between L-band backscatter and biomass is known to saturate at levels commonly observed in forests (Woodhouse et al., 2012). Development of a P-band satellite

remote sensing capability (the BIOMASS mission; Le Toan et al., 2011) should help to alleviate this constraint, as will methods that fuse various types of remotely sensed data (e.g. Mitchard et al., 2012).

We emphasise that the cause-driver linkages used here are hypothetical and are designed to allow exploration of possible futures based on a quite restrictive set of assumptions. This approach is appropriate where the main features of the land use system (i.e. the activities and drivers, and their geographical relations) are not changed in the scenarios, and where interventions are proposed to change existing practices, rather than introducing new land uses. In contrast to these restrictions, which equally apply to alternative statistical simulation approaches, land-use change is often highly non-linear and contingent (Sun et al., 2013). The challenge this poses for land science (Rounsevell et al., 2012) and the creation of REDD+ reference emission levels is an important area for future research. In the meantime, our model, which is not designed to predict anything, but to create scenarios and expose the consequences of assumed linkages under changing drivers, can be used to create simple land-use change and emission reference levels that transparently adjust for national circumstances. This approach could therefore be adopted by countries in the early phases of REDD+ implementation, and refined to give a more accurate estimate of emission reductions and removals as better data become available.

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