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Carbon losses from deforestation and widespread degradation offset by extensive growth in African woodlands

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Vegetation and land use carbon fluxes are major uncertainties in the global carbon cycle. Deforestation and degradation are reducing woody biomass, although tree growth and woody expansion may be counterbalancing these losses. The location and magnitude of these changes remain poorly resolved, particularly in the densely populated savannas and woodlands which dominate the tropics. Here we use radar imagery to quantify degradation and deforestation, and associated aboveground woody carbon stocks (AGC) changes at 25 m resolution across the 2.4 M km² southern African woodlands for 2007-2010. Degradation was widespread, affecting 17.0% of the land area, and, contrary to previous studies, was the source of 55% of carbon losses (-0.075 PgC yr⁻¹). Carbon losses via deforestation were markedly lower (-0.038 PgC yr⁻¹), despite affecting 8.4% of the study area - quadruple existing estimates. Biomass gains occurred in 48% of the region, largely in remote areas, and totalled 0.12 PgC yr⁻¹. Region-wide AGC stocks were therefore stable at 5.5 PgC. These results suggest that land cover in African woodlands is more dynamic than previously thought with globally high rates of deforestation, but also extensive regrowth. Degradation is shown for the first time to be the principal source of biomass loss in the region.

Savanna woodlands, characterised by an open tree canopy and a continuous grass layer, are the dominant vegetation of Southern Africa, and are changing rapidly in response to human activities, with important implications for local livelihoods and the global carbon cycle. Over 150 million people depend on the ecosystem services provided by the woodlands. Rising populations, stagnant yields, altered consumption preferences and new connections to the global economy are thought to be driving widespread deforestation (a reduction in wooded area) mostly due to agricultural expansion, and degradation (a reduction in woody carbon density in an area that remains woodland), often due to harvesting timber or fuel wood. At the same time, several processes are hypothesised to be increasing woody
carbon stocks in the region, including widespread and rapid regrowth following shifting
cultivation\textsuperscript{14}, enhanced tree growth stimulated by increased atmospheric CO\textsubscript{2}
concentrations\textsuperscript{15,16} and reductions in browsing megaherbivores\textsuperscript{17}. However, the location and
rates of these processes, particularly the extent of woody degradation, biomass growth and
regrowth, and the impact of these changes on AGC, remain poorly resolved\textsuperscript{2}.

Addressing these uncertainties is hampered by a lack of knowledge of the carbon-area
(MgC ha\textsuperscript{-1}) density of the woodlands, and its changes over time. Existing coarse resolution
maps of AGC have large discrepancies over African woodlands\textsuperscript{18–20}, whilst the seasonality\textsuperscript{21}
and mixed tree-grass structure of savanna woodlands challenges optical remote sensing
estimates of tree cover change\textsuperscript{4,22}, as green leaf area and reflectance are dynamic and weakly
linked to woody biomass. In addition, many of the current datasets on woodland dynamics,
including the UN Food and Agricultural Organisation’s Forest Resource Assessment (FAO-
FRA)\textsuperscript{8}, present an incomplete picture of woodland and forest dynamics by failing to account
for the low intensity, but widespread, losses occurring in these systems due to wood
harvesting, fire and selective logging\textsuperscript{9,12} (i.e. degradation), or the extent of AGC gains, which
are largely unmeasured\textsuperscript{23}. Obtaining both accurate and spatially explicit estimates of
deforestation, degradation, and biomass (re)growth are crucial to evaluate the response of
savanna woodlands to global change\textsuperscript{24}, and also to support accurate resource assessment, land
management, and the effective targeting and monitoring of land use emission abatement
policies.

Here, we generate the first estimates of the rates, locations and carbon stock changes
associated with degradation and biomass (re)growth across Southern African woodlands, and
provide new, contrasting data on deforestation. These estimates are derived from 25 m
resolution maps of AGC across Southern African for 2007 – 2010, created using a
combination of space-borne L-band radar imagery and field data (Fig. 1). A key advantage of
using radar data is that unlike optical imagery, it is largely insensitive to the intra- and inter-
annual variability in the grass layer and tree leaf phenology\textsuperscript{25}, which can hinder accurate
change detection. Instead, L-band backscatter from ALOS PALSAR\textsuperscript{26} is known to strongly
correlate with woody biomass at multiple sites across African savanna woodlands\textsuperscript{27–29}, where
it has been used to detect small scale changes associated with shifting cultivation and tree
harvesting\textsuperscript{10,13}, as well as areas of increasing biomass at larger scales\textsuperscript{30}. In this paper, we
extend these analyses across the full extent of the Southern African savanna woodlands and
dry forests.
Results
The area of woodland and forest, defined here as pixels with AGC ≥ 10 MgC ha⁻¹ in 2007, was 2.3 M km² (95% CI 2.1–2.5 M km², based on the uncertainty of the biomass–backscatter relationship – see Methods and Supplementary Information). Our estimate is similar to the 2005 estimate from the FAO FRA (Fig. S9), and equates to 50% of the total land area (Table S3), and 10% of the estimated global tropical ‘forested’ area³¹. Nationally, wooded area varies from 33% in Zimbabwe to 55% in Mozambique and Zambia and 62% in the (former) Katanga province of the Democratic Republic of Congo. The mean region-wide carbon density was 24.0 [19.8 – 28.5] MgC ha⁻¹, with the most carbon dense woodlands located in Katanga (mean 28.6 MgC ha⁻¹), and the least dense in Zimbabwe (19.6 MgC ha⁻¹; Fig. 1). Total AGC stocks were approximately constant from 2007-2010 (Fig 1; Table S3), being estimated at 5.51 [4.90 – 6.14] PgC for 2007 and 5.46 [4.8 – 6.10] PgC in 2010, equivalent to 2-3% of the tropical biomass stock¹⁹,³¹, with similar values in 2008 (5.41 PgC) and 2009 (5.42 PgC). Carbon stored in other wooded lands, defined as areas with an AGC density <10 MgC ha⁻¹ in 2007, totalled ~0.7 PgC, however, owing to the higher uncertainty in change detection in low AGC areas, we do not consider these areas further (see Methods).

Our AGC estimates (excluding Katanga) are 61% lower than the FAO FRA⁸, and 66% and 33% lower than the pan-tropical AGC maps of Baccini et al³ and Saatchi et al¹¹ respectively. The recent fusion of multiple datasets by Avitabile et al¹⁹ yielded total AGC estimates similar to our own (+3% [-9 – +12%]), albeit with large spatial differences between the two datasets (Fig. S10), with Avitabile et al. estimating considerably higher stocks in high AGC stands relative to our data, alongside lower estimates in lower density stands.

The aggregate temporal stability in regional carbon stocks between 2007 and 2010 conceals the presence of widespread gross gains and losses, and large differences between the east and west of the region (Fig. 2). Biomass gains were detected in 48% [41– 55%] of the wooded area, with deforestation and degradation occurring in 8.4% [6.4 – 9.9%] and 17.0% [14.0 – 19.7%], respectively (see Methods for a definition of these land cover changes) (Fig. 2).

Degradation rates were highest in Mozambique, Malawi and Tanzania (Fig. 3), with hotspots located near large, rapidly expanding urban centres where woodland resources are scarce (e.g. Dar es Salaam, Luanda and southern Malawi⁹,³², and along transport corridors, ports and some borders (e.g. Beira, Nacala and southern Tanzania)¹⁰,¹³. The spatial pattern suggests these hotspots might be linked to urban demand for biomass energy, or domestic and international timber markets, as opposed to the subsistence needs of the local population⁹,¹⁰,¹³.
Degradation typically reduced AGC from $29 \pm 10 \text{ MgC ha}^{-1}$ (mean $\pm$SD) to $20 \pm 4 \text{ MgC ha}^{-1}$, with degradation disproportionately prevalent in higher biomass woodlands (Fig. 4). This suggests these areas are being targeted for harvesting, probably because they contain trees of suitable size and species for charcoal and timber.

The area affected by deforestation ($193,250 [158,000 – 214,000 \text{ km}^2]$) was around half (49%) the area degraded, with deforestation rates ranging from 1.8% yr$^{-1}$ in Katanga to 4.7% yr$^{-1}$ in Malawi, and exceeding 2% yr$^{-1}$ in the remaining countries (Fig. 3B; Table S4). In contrast to degradation, the vast majority (95%) of deforestation was located in areas with a lower than average AGC density (mean biomass change: $14 \pm 4 \text{ MgC ha}^{-1}$ to $6 \pm 5 \text{ MgC ha}^{-1}$; Fig. 4; Fig. S13)$^{10}$, being particularly prevalent in already fragmented agricultural landscapes, as typified in Fig. 2C, as opposed to the frontier-style deforestation characterised in Fig 2D.

The total area of deforestation estimated here is 4.6 - 5x higher than previous estimates by both the FAO-FRA$^8$ (pro rata for 2005 – 2010, excluding Katanga) and Hansen et al$^4$ for the same time period (2007 – 2010) respectively. This larger deforested area was observed despite our smaller starting estimate of wooded area (due to a stricter “forest” definition; Figure S7), meaning our national percentage deforestation rates are on average 5.9 and 13.8x higher than those of FAO and Hansen (Fig. 3B). These contrasting rates and area estimates are in part due to the differing definitions of forest and deforestation: FAO statistics are based on extrapolated rates of change based on diverse land use classifications, whilst Hansen et al.$^4$ map areas of complete tree cover loss. In contrast, our approach allows for the presence of residual trees in deforested areas$^{10,14}$, with only 10% of our deforested area comprising areas that were completely cleared. We detect deforestation in 59% of the locations where Hansen et al.$^4$ find deforestation, and observe degradation in a further 21%, with the remainder of the Hansen et al deforested area (20%) almost fully accounted for by areas masked from our analysis, or not considered woodland in 2007. In contrast, Hansen et al observed deforestation in only 19% of our deforested areas (Table S2), increasing to 38% when only areas of complete clearance area considered, with most of our ‘extra’ deforestation occurring in areas with low biomass and low tree cover in 2007 (Fig. S13). This suggests our method is more sensitive to changes in more sparsely wooded areas. In such areas, crop or grass biomass strongly influence the optical signal which could lead to deforestation remaining undetected in the Hansen et al product if the removal of trees only weakly affects the land surface reflectance.

Alongside these rapid losses, we also find evidence of widespread gains in biomass $(1.3 \pm 0.9 \text{ MgC ha}^{-1}\text{yr}^{-1}; \text{mean } \pm \text{ SD})$, the magnitude of which is consistent with field data on
regrowth rates\textsuperscript{14}. Biomass increases were more prevalent within relatively low biomass stands, with 60\% of the total gain area in woodlands with AGC <25 MgC ha\textsuperscript{-1} in 2007 (Fig. 4). Widespread gains were also observed in areas that are sparsely populated, and/or have a relatively high mean annual precipitation, including the southern and western parts of Tanzania and Angola, western Zambia and southern DRC (Fig. 2\textsuperscript{11,32,33}). Extensive gains are to be expected given the ubiquity of disturbance in this ecosystem and the typically rapid subsequent regrowth\textsuperscript{14}. However, our finding that regional AGC stocks are roughly constant, despite 24\% of the region being deforested or degraded over the 3-year period, implies some non-equilibrium (re)growth, which may be caused by enhanced disturbance rates prior to the study period (e.g. due to more severe fire regimes in a less fragmented landscape\textsuperscript{12}, or higher elephant densities), possibly combined with enhanced current growth rates (which are predicted under increased CO\textsubscript{2})\textsuperscript{15,16}.

The carbon stock changes (which describe the carbon committed to the atmosphere, a proxy for emissions) associated with deforestation, degradation and (re)growth were estimated by weighting the observed carbon stock changes by the probability of each land cover change having occurred in each pixel. Over the 3-year period, biomass changes due to (re)growth were 0.35 [0.29 – 0.42] PgC with losses totalling 0.41 [0.34 – 0.48] PgC, of which deforestation contributed 0.11 [0.08 – 0.14] PgC, and degradation 0.22 [0.17 – 0.27] PgC, or 66\% [60-70\%] of the likely anthropogenic (deforestation + degradation) carbon losses (Fig. 3C). There were large variations in carbon dynamics across the region, with net reductions in Mozambique (-3.4\% of 2007 AGC stock), Tanzania (-4.8\%) and Malawi (-4.9\%), and gains in Angola (+1.5\%) and Zambia (+1.0\%) (Fig. 3C).

The small net change in AGC observed here (-0.02 PgC yr\textsuperscript{-1}) contrasts with FAO-FRA\textsuperscript{8} statistics which suggest a more rapid reduction in stocks across the study region (-0.08 Pg yr\textsuperscript{-1}; 2005-2010), probably because our dataset better accounts for biomass gains (Table S3). Our estimate of gross AGC losses from deforestation and degradation (0.11 PgC yr\textsuperscript{-1} [0.09 – 0.14] PgC yr\textsuperscript{-1}) is 6x higher than that obtained from overlaying the most widely used maps of forest change (Hansen\textsuperscript{4}) and carbon stocks (Avitabile\textsuperscript{19}) (0.016 PgC yr\textsuperscript{-1}). These boosted carbon emissions primarily reflect the incorporation of degradation losses, but also the higher deforestation area, and differences in the carbon density of land undergoing change. Our estimated gross anthropogenic AGC losses are similar to those released from deforestation in the more spatially extensive Brazilian Amazon (0.18 Pg yr\textsuperscript{-1})\textsuperscript{34}, and are equivalent to 4 - 10\% of the current estimated gross tropical land-use emissions\textsuperscript{3,5,6}, indicating the importance of these woodlands for the global climate system.
**Discussion**

Overall, our results present a picture of highly dynamic land cover change across the region, with rapid deforestation and degradation underway in hotspots around population centres, counterbalanced by woody biomass increases in remote areas. In this analysis we exclude areas that were non-wooded in 2007, which precludes the estimation of non-forest carbon gains and losses, including wooded area expansion, which could also be widespread. Degradation, which has never been quantified at this scale, nor in such a spatially explicit manner, is the main cause of biomass loss, being particularly prevalent in higher biomass areas, which are often floristically diverse and of high conservation value. African savanna woodlands are unique in that they retain significant wooded area and biomass, alongside a high human population closely dependant on woodland resources. Thus, large degradation losses may be a unique feature of African woodlands, but are still large enough to impact global land use emissions.

Our finding of high carbon losses from degradation presents several challenges to attempts to reduce carbon emissions from deforestation and degradation (REDD+). Firstly, most efforts have focussed on avoided deforestation in intact woodlands, whereas we show that degradation, and deforestation in low biomass, mosaic landscapes, are the critical processes. This mis-targeting is potentially costly, as for many regulating and provisioning ecosystem services, the “last” tree to be felled is much more valuable than the “first”. Secondly, since degradation is difficult to monitor, most REDD+ policy and practice has been created with little data on the rates and locations, and thus causes, of degradation. This links to a further challenge identified here: the spatial pattern of degradation indicates that it is mostly driven by distal actors, and probably linked to demand for energy and timber in urban areas, or abroad. Locally driven, rural demand is unlikely to be a useful intervention point for mitigation, which should instead focus on urban and international value chains and demand.

Our results also highlight the extent of biomass (re)growth across these woodlands, which counterbalance the carbon losses. The dominant miombo and mopane woodlands have long been subjected to, and thus are highly adapted to, disturbance by hominids, fire, elephants and other browsers. Many of these disturbance agents have declined markedly due to urban migration, defaunation, and landscape fragmentation, which may explain some of the widespread gains observed in more remote, rural areas. Thus, the disturbances which are found to be widespread around population centres may have replaced these quasi-natural losses. The critical issues to maintaining ecosystem service provision and carbon storage is...
therefore the post disturbance land use, as when woodlands are not fully transformed, they can recover their biomass within three decades of clearance\textsuperscript{14}, meaning they can support some level of clearing in perpetuity. Continued monitoring of these systems is needed to evaluate the permanence of these land cover changes, and to evaluate the impacts of changes in climate and atmospheric CO\textsubscript{2} concentrations – drivers which are likely to have contrasting effects on woody cover over the next century\textsuperscript{38}.

The methods presented here are not specific to the radar satellite used (ALOS PALSAR), and are applicable to longer wavelength radar sensors, including the P-band BIOMASS mission\textsuperscript{39} designed to estimate biomass in more carbon dense moist tropical forests, and the planned L-band SAOCOM-1 and NISAR missions\textsuperscript{40}. Future monitoring efforts will need to incorporate repeat \textit{in situ} observations of both AGC growth and loss to corroborate remotely sensed estimates of change – something that is not possible here due to the lack of region-wide contemporaneous measurements of biomass change. Future work should also focus on understanding the drivers of woodland loss, and the effectiveness of protected areas in reducing land use change.

\textbf{Methods}

We evaluated change in biomass by creating a time series (2007-2010) of aboveground woody carbon (AGC) maps at 25 m resolution covering the study region. Maps were produced using a combination of satellite radar images and \textit{in situ} carbon stock estimates for calibration. We use the Horizontal send-Vertical receive (HV) backscatter mosaics from the Japanese Aerospace Exploration Agency (JAXA) Advanced Land Observing Satellite Phased Array type L-band Synthetic Aperture Radar (ALOS PALSAR), which are geometrically and radiometrically corrected\textsuperscript{26}. L-band HV backscatter is known to be sensitive to woody biomass density up to a saturation point of around 75 MgC ha\textsuperscript{-1} and has been shown to be able to detect deforestation, degradation, and regrowth in savanna woodlands\textsuperscript{10,13,27}. Radar backscatter, particularly at low woody biomass, is affected by soil moisture, which can enhance backscatter relative to dry conditions and reduce the distinction between wooded and bare areas. To account for seasonal moisture effects, we developed a statistical model that applies a small correction to the backscatter data in areas where the estimated soil moisture varied between years. The model provides for differential corrections according to the estimated woody biomass, following the logic of the Water Cloud Model\textsuperscript{41}. Areas where soil moisture varied markedly between 2007 and 2010 observations (e.g. when
the data was collected at very different times of the year) were removed from the analysis
(2% of land area). We also exclude areas from the analysis likely to have elevated moisture,
or be seasonally flooded, including areas near rivers, water bodies, deltas, and irrigated
croplands (11% of the total land area). We do not include non-woodland lands (<10 MgC ha\(^{-1}\)
in 2007) in our change analysis as soil effects in these areas are likely to be strong\(^{10,42}\).

To generate maps of AGC, we regressed mean backscatter \(\gamma^0\) (in natural units, not
dB) against the equivalent field measured carbon stocks at 137 sites in Malawi, Mozambique
and Tanzania (median plot size 0.6 ha), from which we derived a general model (AGC =
715.67 \times \gamma^0 – 5.97; \(r^2 = 0.57\); RMSE = 8.5 MgC ha\(^{-1}\); bias = 1.1 MgC ha\(^{-1}\)), which we use to
convert radar backscatter to maps of AGC (See supplementary information). The RMSE
represents the error on a prediction of biomass for a single pixel, which decreases as pixels
are aggregated together (i.e. RMSE is minimal at the scale of the districts that we report
here). However, bias is a separate quantity from RMSE and does not cancel out. As such, bias
is the main source of uncertainty in biomass estimation at regional scales\(^{10}\).

We assume that the biomass-backscatter relationship is consistent over time. The
assumption of an invariant physical relationship between the remotely sensed observation and
land surface is common among change detection studies using radar and other
sensors\(^{10,23,32,43}\). In our case, there is no reason to dispute this assumption given that soil
moisture impacts have largely been accounted for, and the stability of the sensor response
over time has been verified\(^{26}\), meaning any changes in backscatter are likely to be related to
changes in land cover.

The AGC maps were then used to estimate the occurrence of the four land-cover-
change (LCC) processes of interest, identified by comparing pixel carbon densities in 2007
and 2010. These LCC processes are: clearance

1) Deforestation (more properly, the loss of wooded areas), where a pixel loses more
than 20% of its biomass and moves from above the “forest” or wooded threshold
of 10 MgC ha\(^{-1}\) in 2007, to below the threshold in 2010;
2) Degradation, where a woodland pixel again loses more than 20% of its biomass
but does not cross the non-wooded threshold and so remains woodland;
3) Minor losses, where a pixel loses <20% of its biomass; and
4) Growth, where a pixel increases in biomass from 2007 to 2010. We describe this
using the term ‘(re)growth’, as this process includes both woodland regrowing
after disturbance, and biomass increases in intact woodland.
Previous studies\textsuperscript{13,30} have shown that changes in biomass <20\% of the 2007 AGC value (i.e. ‘minor losses’) were rarely directly caused by humans. In contrast, losses above this threshold correspond to areas impacted by harvesting for timber and wood fuel or cleared for agriculture\textsuperscript{13,30}. Our definition of deforestation is designed to better capture areas converted to small scale agriculture by allowing for some residual woody biomass in the post clearance land cover - a common feature of the typically low-input, shifting agriculture that is widely practiced in the region\textsuperscript{14}. Shifting cultivators commonly leave large trees standing in their fields due to the disproportionate effort involved in their felling, or because the tree provides other ecosystem services, but as the resultant land cover is primarily agricultural, such land is properly classified as deforested.

To estimate the area and carbon emissions associated with each LCC process, we adopt a probabilistic approach that is specifically designed to account for the random errors that contribute to the high RMSE, rather than a binary classification of change according to the most likely LCC scenario, e.g. degraded / not degraded. A probabilistic approach is suited to biomass maps derived from synthetic aperture radar (SAR) imagery given the noise-like phenomenon of speckle that is inherent to this type of data. Speckle arises because of interference between the signal from scatterers within a pixel, and leads to a well characterised distribution of observed backscatter, even over homogenous areas\textsuperscript{44}. Any error distributions in backscatter will also present in biomass maps, and could signal false LCC events when biomass maps from different time points are compared directly. If not accounted for, speckle would lead to an overestimation of land cover change; thus, we developed a statistical model that accounts for both the speckle-induced changes in backscatter, and the uncertainty on the regression model used to convert backscatter to biomass (see Supplementary Information section 2.6). This model conservatively estimates the probability that a real LCC has occurred.

The area affected by each LCC is calculated by summing the probabilities of each LCC having occurred in a single pixel, appropriate given there is no spatial pattern to speckle. To estimate the carbon stock changes caused by each of the LCC processes of interest, observed changes in AGC stocks between 2007 and 2010 are weighted by the probability that each land cover change has occurred.

Uncertainties on all quantities were estimated through the propagation of the uncertainty in the biomass-backscatter relationship, including the bias. We employed a 5000 x 2-fold cross-validation procedure\textsuperscript{10}, withholding half of the ground data used to calibrate the radar data, and using the remainder to generate the biomass-backscatter relationship. This
Uncertainty procedure was applied to a random subsample of 5% of the study area, comprising 2000 x 100 km² areas randomly distributed across the study area. For each area, we calculated all derived quantities, retaining the 2.5th and 97.5th percentiles of the 5000 estimates, and using these 95% CI to approximate the uncertainties over the whole study area.

A more detailed description and justification of our methods, along with additional results, including a breakdown of change statistics by major administrative unit, is available in Supplementary Information.

References

1. Grace, J., Mitchard, E. & Gloor, E. Perturbations in the carbon budget of the tropics. *Glob. Chang. Biol.* 3238–3255 (2014). doi:10.1111/gcb.12600
2. Valentini, R. et al. A full greenhouse gases budget of Africa: synthesis, uncertainties, and vulnerabilities. *Biogeosciences* **11**, 381–407 (2014).
3. Baccini, A. et al. Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. *Nat. Clim. Chang.* **2**, 182–185 (2012).
4. Hansen, M. C. et al. High-resolution global maps of 21st-century forest cover change. *Science* **342**, 850–3 (2013).
5. Pan, Y. et al. A large and persistent carbon sink in the world’s forests. *Science* **333**, 988–93 (2011).
6. Le Quéré, C. et al. Global Carbon Budget 2015. *Earth Syst. Sci. Data* **7**, 349–396 (2015).
7. Pearson, T. R. H., Brown, S., Murray, L. & Sidman, G. Greenhouse gas emissions from tropical forest degradation: an underestimated source. *Carbon Balance Manag.* **12**, 3 (2017).
8. Food and Agriculture Organization of the United Nations (UN FAO). *Global Forest Resources Assessment*. (2015).
9. Ahrends, A. et al. Predictable waves of sequential forest degradation and biodiversity loss spreading from an African city. *Proc. Natl. Acad. Sci. U. S. A.* **107**, 14556–14561 (2010).
10. Ryan, C. M. et al. Quantifying small-scale deforestation and forest degradation in African woodlands using radar imagery. *Glob. Chang. Biol.* **18**, 243–257 (2012).
11. Mitchard, E. T. a & Flintrop, C. M. Woody encroachment and forest degradation in sub-Saharan Africa’s woodlands and savannas 1982–2006. *Philos. Trans. R. Soc. B Biol. Sci.* **368**, 20120406 (2013).
12. Andela, N. & van der Werf, G. R. Recent trends in African fires driven by cropland expansion and El Niño to La Niña transition. *Nat. Clim. Chang.* **4**, 791–795 (2014).
13. Ryan, C. M., Berry, N. J. & Joshi, N. Quantifying the causes of deforestation and degradation and creating transparent REDD+ baselines: A method and case study from central Mozambique. *Appl. Geogr.* **53**, 45–54 (2014).
14. McNicol, I. M., Ryan, C. M. & Williams, M. How resilient are African woodlands to disturbance from shifting cultivation? *Ecol. Appl.* **25**, 2330–2336 (2015).
15. Bond, W. J. & Midgley, G. F. Carbon dioxide and the uneasy interactions of trees and savannah grasses. *Philos. Trans. R. Soc. B Biol. Sci.* **367**, 601–612 (2012).
16. Higgins, S. I. & Scheiter, S. Atmospheric CO2 forces abrupt vegetation shifts locally, but not globally. *Nature* **488**, 209–12 (2012).
17. Hempson, G. P., Archibald, S. & Bond, W. J. A continent-wide assessment of the form and intensity of large mammal herbivory in Africa. *Science* (80-.). **350**, 1056–1061 (2015).

18. Mitchard, E. T. *et al.* Uncertainty in the spatial distribution of tropical forest biomass: a comparison of pan-tropical maps. *Carbon Balance Manag.* **8**, 10 (2013).

19. Avitabile, V. *et al.* An integrated pan-tropical biomass map using multiple reference datasets. *Glob. Chang. Biol.* **22**, 1406–1420 (2016).

20. Hill, T. C., Williams, M., Bloom, a A., Mitchard, E. T. a & Ryan, C. M. Are inventory based and remotely sensed above-ground biomass estimates consistent? *PLoS One* **8**, e74170 (2013).

21. Ryan, C. M., Williams, M., Hill, T. C., Grace, J. & Woodhouse, I. H. Assessing the Phenology of Southern Tropical Africa: A Comparison of Hemispherical Photography, Scatterometry, and Optical/NIR Remote Sensing. *IEEE Trans. Geosci. Remote Sens.* **52**, 519–528 (2013).

22. Achard, F. *et al.* Determination of tropical deforestation rates and related carbon losses from 1990 to 2010. *Glob. Chang. Biol.* **20**, 2540–2554 (2014).

23. Brandt, M. *et al.* Human population growth offsets climate-driven increase in woody vegetation in sub-Saharan Africa. *Nat. Ecol. Evol.* **1**, 81 (2017).

24. Poulter, B. *et al.* Contribution of semi-arid ecosystems to interannual variability of the global carbon cycle. *Nature* **509**, 600–603 (2014).

25. Archibald, S. & Scholes, R. Leaf green-up in a semi-arid African savanna-separating tree and grass responses to environmental cues. *J. Veg. Sci.* **18**, 583–594 (2007).

26. Shimada, M. *et al.* New global forest / non-forest maps from ALOS PALSAR data (2007–2010). *Remote Sens. Environ.* **155**, 13–31 (2014).

27. Mitchard, E. T. A. *et al.* Using satellite radar backscatter to predict above-ground woody biomass: A consistent relationship across four different African landscapes. *Geophys. Res. Lett.* **36**, (2009).

28. Mermoz, S., Le Toan, T., Villard, L., Réjou-Méchain, M. & Seifert-Granzin, J. Biomass assessment in the Cameroon savanna using ALOS PALSAR data. *Remote Sens. Environ.* **155**, 109–119 (2014).

29. Mermoz, S. *et al.* Decrease of L-band SAR backscatter with biomass of dense forests. *Remote Sens. Environ.* **159**, 307–317 (2015).

30. Mitchard, E. T. a. *et al.* A novel application of satellite radar data: measuring carbon sequestration and detecting degradation in a community forestry project in Mozambique. *Plant Ecol. Divers.* **6**, 159–170 (2013).

31. Saatchi, S. S. *et al.* Benchmark map of forest carbon stocks in tropical regions across three continents. *Proc. Natl. Acad. Sci. U. S. A.* **108**, 9899–904 (2011).

32. Liu, Y. Y. *et al.* Recent reversal in loss of global terrestrial biomass. *Nat. Clim. Chang.* **5**, 1–5 (2015).

33. Frost, P. & Campbell, B. M. in *The Miombo in transition: Woodlands and welfare in Africa* (ed. Campbell, B. M.) 11–55 (Center for International Forestry Research, 1996).

34. Song, X. P., Huang, C., Saatchi, S. S., Hansen, M. C. & Townshend, J. R. Annual carbon emissions from deforestation in the Amazon basin between 2000 and 2010. *PLoS One* **10**, 1–21 (2015).

35. Baccini, A. *et al.* Tropical forests are a net carbon source based on aboveground measurements of gain and loss. *Science* (80-.). **358**, 230–234 (2017).

36. McNicol, I. M., Ryan, C. M., Dexter, K. G., Ball, S. M. J. & Williams, M. Aboveground carbon storage and its links to forest structure, tree species diversity and floristic composition in south-eastern Tanzania. *Ecosystems* (2017). doi:10.1007/s10021-017-0180-6
37. Hosonuma, N. et al. An assessment of deforestation and forest degradation drivers in developing countries. *Environ. Res. Lett.* 7, 44009 (2012).

38. Ryan, C. M., Pritchard, R., McNicol, I., Lehmann, C. & Fisher, J. Ecosystem services from Southern African woodlands and their future under global change. *Philos. Trans. R. Soc. Lond. B. Biol. Sci.* (2016).

39. Le Toan, T. et al. The BIOMASS mission: Mapping global forest biomass to better understand the terrestrial carbon cycle. *Remote Sens. Environ.* 115, 2850–2860 (2011).

40. Reiche, J. et al. Combining satellite data for better tropical forest monitoring. *Nat. Clim. Chang.* 6, 120–122 (2016).

41. Attema, E. P. W. & Ulaby, F. T. Vegetation modeled as a water cloud. *Radio Sci.* 13, 357 (1978).

42. Lucas, R. et al. An evaluation of the ALOS PALSAR L-band backscatter - Above ground biomass relationship Queensland, Australia: Impacts of surface moisture condition and vegetation structure. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* 3, 576–593 (2010).

43. Mitchard, E. T. a. et al. Measuring biomass changes due to woody encroachment and deforestation/degradation in a forest–savanna boundary region of central Africa using multi-temporal L-band radar backscatter. *Remote Sens. Environ.* 115, 2861–2873 (2011).

44. Oliver, C. & Quegan, S. *Understanding Synthetic Aperture Radar Images.* (1998).

45. CIESIN, IFPRI, World Bank & CIAT. Global Rural-Urban Mapping Project, Version 1 (GRUMPv1): Population Count Grid. *NASA Socioeconomic Data and Applications Center (SEDAC)* (2011). doi:10.7927/H4R20Z93

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**Author contributions**

IMM and CMR conceived the idea for the paper, and devised the methodology with input from EM. IMM processed and analysed the data. CMR developed the speckle model and probabilistic approach for detecting change with input from IMM. IMM and CMR led the writing of the manuscript with input from EM. All authors gave final approval for submission.

**Competing financial interests**

We confirm that there are no conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced our conclusions.
Figure 1 | Spatial distribution of aboveground woody carbon stocks in 2007, estimated from L-band radar data and in situ measurements. The main map shows the mean carbon density, averaged to 1 km² for display purposes, with non-wooded areas (<10 MgC ha⁻¹) and other areas masked from the analysis in grey. The upper and side panels show the frequency distribution of aboveground woody carbon stocks for each country (including the woodland dominated former Katanga Province of the DRC) from 2007 – 2010 with the vertical lines indicating the yearly mean.
Figure 2 | Change in above ground carbon stocks between 2007 and 2010. The main figure (A) shows the average percentage change in AGC at 1 km resolution. Areas masked from the study due to soil moisture differences between years are masked by the white stripes, whilst irrigation or urban land covers are masked in grey (see Supplementary material for details). Human population density and centres (B) are from GRUMP. The sub figures C - E are at 25 m resolution and illustrate three important syndromes of land cover change: C) the deforestation (red) of small areas of woodland in an already largely deforested area of Tanzania (“mopping up”), D) the progression of the agricultural frontier and associated deforestation and degradation (blue) to the north of Lichinga city in Mozambique, and E) the extensive degradation in frontier regions of Mozambique near to the demand centres of southern Malawi, suggestive of cross border flows of biomass energy.
Figure 3 | Woodland area and carbon stock changes separated by nation/region. (A) Percentage of the wooded area in 2007 affected by deforestation, degradation, minor losses and (re)growth (B) Comparison between existing estimates of deforestation rates and this study (C) Carbon stock changes due to deforestation, degradation and (re)growth. Error bars show the 95% CIs and represent for the total error on each bar.
Figure 4 | Area of land cover change by the initial carbon density. A) The cumulative contribution of different AGC classes (in 5 MgC ha\(^{-1}\) bins) to the total area of woodland, and each land cover change. B) The proportion of woodland areas in 2007 that were affected by each land cover change. The hatched horizontal lines indicate the proportion of the total woodland area affected.