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Detecting and predicting forest degradation: A comparison of ground surveys and remote sensing in Tanzanian forests

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Detecting and predicting forest degradation: A comparison of ground surveys and remote sensing in Tanzanian forests

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Summary

- Tropical forest degradation is widely recognised as a driver of biodiversity loss and a major source of carbon emissions. However, in contrast to deforestation, the more gradual changes from degradation are challenging to detect, quantify, and monitor. Here we present a field protocol for rapid, area-standardised quantifications of forest condition, which can also be done by non-specialists. Using the example of threatened high-biodiversity forests in Tanzania, we analyse and predict degradation based on this method. We also compare the field data to optical and radar remote sensing datasets, thereby conducting a large-scale, independent test of the ability of these products to map degradation in East Africa from space.
- Our field data consist of 551 'degradation' transects collected between 1996 and 2010, covering >600 ha across 86 forests in the Eastern Arc Mountains and coastal forests.
- Degradation was widespread, with over one third of the study forests – mostly protected areas – having more than 10% of their trees cut. Commonly-used optical remote-sensing maps of complete tree cover loss only detected severe impacts (≥25% of trees cut), i.e. a focus on remotely sensed deforestation would have significantly underestimated carbon emissions and declines in forest quality. Radar-based maps detected even low impacts (<5% of trees cut) in ~90% of cases. The field data additionally allowed to differentiate different types and drivers of harvesting, with spatial patterns suggesting that logging and charcoal production were mainly driven by demand from major cities.

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- Rapid degradation surveys and radar remote sensing can provide an early warning and guide appropriate conservation and policy responses. This is particularly important in areas where forest degradation is more widespread than deforestation, such as in east and southern Africa.

Key words

Carbon Emissions; Community-based Forest Management; East Africa; Biodiversity Conservation; Global Forest Watch; Human Disturbance; Synthetic Aperture Radar; Village Land Forest Reserves

Societal Impact Statement

Vast areas of tropical forest are degraded. Whilst a lot of progress has been made with assessing deforestation from space, quantifying degradation remains challenging. Thus, whilst global tree cover is being mapped with increasing accuracy, much less is known about the quality of that tree cover. Here we present a field protocol for rapid assessments of forest condition. Using extensive field data from Tanzania we show that a focus on remotely-sensed deforestation on its own would not detect significant reductions in forest quality, while radar-based remote-sensing of degradation had good agreement with the ground data. The ground data provided additional insights into the nature and drivers of degradation, an understanding of which is vital to conserving forest resources and ensuring their long-term support of ecosystem services. We recommend the use of rapid field assessments in combination with remote sensing to provide an early warning, and to allow timely and appropriately targeted policy responses.

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Introduction

Large areas of tropical forest are degraded through human impacts such as overexploitation, fragmentation, pollution, exotic species invasion and fire (Sloan and Sayer, 2015). While there is no globally agreed definition for forest degradation, it can be broadly defined as changes to a forest stand resulting in the long-term reduction of particular attributes and functions, such as biodiversity, and the potential supply of goods and services (FAO, 2011; Ghazoul et al., 2015). Deforestation – the complete replacement of forest by another land use – is easier to define, detect and monitor, and consequently has been the focus of global policy development (Sasaki and Putz, 2009). As a result, the impacts of forest degradation on biodiversity and carbon balances are comparatively poorly understood, but they are likely to be significant (Alroy, 2017). For instance, recent studies have shown that carbon emissions from forest degradation may have been underestimated and could account for as much as 25-69% of the combined gross carbon losses due to deforestation and degradation in the tropics (Baccini et al., 2017; Berenguer et al., 2014; Pearson et al., 2017).

Significant progress has been made with measuring deforestation and forest degradation from space (Woodcock et al., 2020). Changes in tree cover and biomass can now be monitored at high spatial and temporal resolution, providing policy makers and conservation planners with an unprecedented wealth of data to guide interventions (Blackman, 2013; DeVries et al., 2015; Fuller, 2006). The technology is also increasingly available to non-specialists (Asner, 2009). Whilst there are many easily accessible datasets to assist national and global monitoring of forest cover (e.g. Hansen et al., 2013; Miettinen et al., 2011; Sexton et al., 2013), remotely-sensed forest degradation data are sparser and more challenging to obtain. At a country level, quantitative assessments of degradation are often lacking (Romijn et al., 2015). Radar data hold particular promise as they overcome the challenges presented by cloud cover and variable phenology, and they correlate with changes in biomass (McNicol et al., 2018; Mitchell et al., 2017; Ryan et al., 2012). However, using such data sources for detecting and quantifying degradation from space remains limited by the extent to which degradation is associated with a reduction in canopy cover and/or biomass (Ryan et al., 2012). Airborne radar and Light Detection and Ranging (LiDAR; Ene et al. (2017)), as well as the use of unmanned aerial vehicles (Baena et al., 2018; Ota et al., 2019) can provide higher resolution data, but these technologies require expertise, lack global coverage and historical archives, and can be prohibitively expensive. Ground-based sensing methods such as hemispherical photographs (Fournier and Hall, 2017) and terrestrial LiDAR (Decuyper et al., 2018) are also increasingly

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used to quantify stand structural attributes also hold promise, but again, using these technologies requires expertise.

At the other end of the spectrum there are detailed field assessments (Thompson et al., 2013), such as permanent sample plots for assessing changes in forest vegetation. Collecting data on species, stem diameter, height, crown cover and various biotic and abiotic parameters, they are an extremely important tool in biodiversity and environmental research (Baker et al., 2017), and are used to locally characterise biodiversity, growing stock, biomass, carbon, ecosystem function, and impacts of degradation. However, permanent plots are also labour intensive and time consuming to set up, and surveying them requires expertise. Consequently, few countries conduct exhaustive plot-based inventories as part of their national forest reporting, and even fewer consistently monitor them (FAO, 2011). In addition, whilst permanent plots are essential to understand the *impacts* of degradation, they are often not the most effective method to understand the extent and patterns of degradation itself. Unless they are systematically placed to cover an entire area at high density, they rarely capture the breadth of degrading activities that occur. On the contrary – the presence of researchers and permanent tags on trees may deter illegal activities. Plots are also often placed in a stratified random or subjective fashion, i.e. purposefully located in pre-selected areas viewed as representative of a given vegetation type and/or level of disturbance. In addition, as degradation is generally not the main focus, it is often not quantified in a robustly comparable and systematic way.

Consequently, whilst countries increasingly monitor wall-to-wall forest cover change using remote sensing, and they also have some inventory data, they still lack representative quantitative data on forest degradation (Romijn et al., 2015). Difficulties with monitoring forest degradation and associated gaps in policy interventions create opportunities for unregulated and/or illegal logging and corruption. There can be a tendency to shift the blame for forest loss among actors, whereby existing prejudice against already marginalised groups such as farmers practising shifting cultivation or charcoal producers may be reinforced (Hosonuma et al., 2012; Ryan et al., 2014). Knowledge of which forests are degraded, where degradation is likely to spread to next, and what the main drivers are is vital for formulating appropriately targeted policy interventions and management.

Here we present a framework protocol for rapid area-standardised assessments of forest condition. The protocol sits in the middle of the spectrum between detailed ground surveys and

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remote sensing, and its implementation does not require professional training. The protocol assesses human use and disturbance, which depending on their levels and the forest type may lead to a deterioration of stocks and services, and thus degradation.

Using the example of threatened and highly biodiverse forests in Tanzania we investigate

(1) how ground data collected using this protocol compare to remotely-sensed datasets; specifically, radar-based maps of biomass change (McNicol et al., 2018) and commonly used maps of complete tree cover loss (which underpin 'Global Forest Watch'; Hansen et al., 2013);
(2) the value of ground data for understanding and predicting degradation in combination with spatially explicit models (for example, whether data collected using this approach in 1996-2010 could have predicted human impacts in 2020).

The overall aim is to assess whether these rapid assessments are a useful addition to remote sensing and detailed vegetation assessments in (permanent) plots in informing conservation policy and practice.

Methods

Protocol overview

The method presented here rapidly quantifies standing woody resources and resource extraction in forests with a view to gauging forest condition (Frontier Tanzania, 2001). While the protocol is flexible and can be adjusted to the target vegetation and area, the assessment obviously needs to be standardised to facilitate comparisons. The assessment is done along transects, which typically have a width of 10 m. Their length is variable and can be adjusted to the target vegetation type and forest size. The transects are located in either a random, stratified random, or systematic fashion, and should cover the forest edge as well as the interior. Within each transect all trees, as well as stumps and other signs of human use (such as charcoal production or clearance for agriculture) are recorded. The minimum assessment threshold is typically 5 cm diameter at breast height (dbh; measured 1.3 m above ground), but this can be adjusted to the type of vegetation being surveyed. In its simplest form the method focusses on assessing the number of cut trees versus those that are (left) standing or died naturally. Size categories can be added to distinguish cutting for different end uses. Depending on the aims of the sampling, recording can be simple counts within categories, or include more detailed information such as diameter (over bark), height, species identification, and voucher collection. Identifying at least the commonly-used timber species will indicate resource preference and

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hint at the likely nature of the market behind that – e.g. whether trees are cut for local use or international export (Furukawa et al., 2011) (fully noting that timber trade names often refer to collectives of species and/or an entire genus, i.e. overharvesting of individual species can be masked when using trade names only). However, the time spent collecting, measuring and identifying trades off against the primary aim of the method – to rapidly cover many areas, often with the help of non-specialists, in order to obtain reasonably reliable estimates of degradation and to support the identification of areas in need of conservation interventions. A detailed protocol and a recommended set of core measurements are provided as part of the Supporting Information.

Example application

Study Area

The study area (see also Methods S1) spans the Eastern Arc Mountains and part of the coastal forests, both of which are of global importance for biodiversity conservation due to high levels of localised endemism (Mittermeier et al., 2011; Olson and Dinerstein, 2002; Stattersfield, 1998). These forests systems also provide critical ecosystem services to local communities and the nation as a whole (Ashagre et al., 2018; Fisher et al., 2011; Schaafsma et al., 2014; Swetnam et al., 2011). In southern Africa (here defined as roughly -1^{0} to -34^{0} latitude) the livelihoods of an estimated 150 million people are thought to be dependent on the goods and services provided by woodlands and forests (Ryan et al., 2016). Rapid urbanisation and population growth mean that demand for wood products is substantial and increasing, with fuel wood being the main source of energy for over 90% of the population (Bailis et al., 2005). The Tanzanian forestry sector – both formal and informal - is also an important source of income, GDP, and employment (Doggart et al., 2020; United Republic of Tanzania, 2001). Whilst the trade in wood products is often small-scale and livelihood driven (Cavanagh et al., 2015), wood is also exported to generate foreign revenue (Lukumbuzya and Sianga, 2017). Exact figures are difficult to obtain (Lukumbuzya and Sianga, 2017), but although Tanzania has a comprehensive legal framework for the conservation and management of forest resources, and although the forests studied here mostly occur in protected areas, overharvesting is likely to be widespread (Milledge et al., 2007). An ability to monitor and to identify drivers and patterns of forest loss and degradation is vital to the conservation of these forest systems, and to ensure the long-term provision of forest resources for sustainable livelihoods.

Field data

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The data used for this example application were collected between 1996 and 2010 (median 2004-2005) by a wide range of institutions and individual collectors (see Acknowledgements). In total there were 551 transects of 10 m width with a combined length of 609 km from 86 forests. The transects were placed in either a systematic or stratified random fashion to sample both easily accessible and remote areas (Fig. 1a). All transects recorded standing, naturally dead and cut trees in two size categories: 'poles' (=slender stems frequently used in house construction; ≥5 – 15 cm dbh), and 'trees' (>15 cm dbh). In total 430,116 stems and stumps were recorded. Stumps were classed into two age categories: recent (generally cut ≤6 months prior to observation) or old, and records were made of all other types of extractive activities such as the presence of charcoal kilns. A small subset of transects (n=45 covering 18.75 ha in the coastal forests; Ahrends et al., 2010) made more detailed assessments, including exact dbh measurements and species identification. For spatially explicit analyses (comparison with remotely sensed datasets and modelling) we excluded 11 transects where the length and/or locality description did not match the length or locality given by GPS coordinates.

Comparison with remotely-sensed datasets

We compared the ground data against two remotely-sensed datasets:

(1) widely used maps for tree cover loss produced by the initiative 'Global Forest Watch' (Hansen et al., 2013), hereafter GFW, which are based on Landsat data and assess complete canopy loss at an approximate resolution of 28 m on the ground;

(2) a radar based dataset (McNicol et al., 2018) (hereafter MN18), which uses a probabilistic approach to map deforestation and degradation in southern Africa between 2007 and 2010 based on L-Band radar from ALOS-PALSAR; MN18 averaged the data from a resolution of 25 m to 100 m. We focussed on cells with a probability ≥0.5 of degradation or deforestation.

For both comparisons we looked at buffers of up to 100 m around transects. The ground data were restricted to the relevant period of satellite data acquisition (2000-2005 for comparisons to GFW, and 2007-2010 for comparisons to GFW and MN18). Only 'recent' stumps (i.e. stumps no older than 6 months) were included. Degradation counted as 'detected' if the remotely-sensed data reported a pixel as degraded or deforested anywhere within that buffer. Here we focus on true positives only. Due to widespread harvesting it was not possible to assess the rate of false positives, which however has equally important implications for the practical application of these datasets.

Modelling and predicting degradation

We used a spatially explicit modelling approach to investigate which factors were most influential in explaining the spatial patterns of degradation, and whether the spread was predictable. Models were developed using Boosted Regression Trees – an ensemble method, which combines regression trees and boosting, and fits multiple simple regression trees in a forward iterative fashion. The algorithm is able to fit complex non-linear patterns and interactions, and handles different type of predictor variables (Elith et al., 2008). We focussed on three dependent variables: (1) density of charcoal kilns, (2) percentage of poles (stems ≥5-15 cm dbh) cut, and (3) percentage of trees (>15 cm dbh) cut. A transect constituted an individual data point. For modelling the percentage of trees cut we discarded transects with an overall tree density <50 ha^{-1} and no reported logging (n=25), assuming that in these areas there were hardly any trees to be cut in the first place. We considered 15 candidate predictors representative of physical accessibility, likely demand, availability of resources, forest management type and tenure (Tables S1 and S2). For each dependent variable we tested eight models with different (pre-selected) combinations of predictors (Table S3), including a correction for spatial autocorrelation. The final models were selected based on model performance when validated against test data (cross-validation correlations on up to 25% of randomly set aside test data) and maximum parsimony in terms of the number of predictors used (Table S4). Further details on model settings, parameterisation and performance are summarised in Tables S3-5, and software notes are provided in Methods S2. In order to test the predictive ability of the models we extrapolated them at 1 km resolution for all ~12,000 km^2 of forest reserves in the study area, using predictor values for 2020 (from scenarios developed in 2010; Swetnam et al. (2011)). These scenarios (broadly correctly) predicted population to increase at a rate of 3% annually, but they are conservative in that they did not make predictions around infrastructure expansion. The predictions were then compared to actual tree cover losses recorded by GFW and local reports on degradation.

Results

Observed rates of tree cutting

Tree cutting (here ≥5 cm dbh; see Notes S1 for trees >15 cm dbh only) occurred in all but one forest between 1996 and 2010. Over one third of forests surveyed during this time had at least 10% of trees ≥5 cm dbh cut (mean among transects). Rates were very variable across forests, ranging from 0-81% with a mean of 10% (±15% SD) and a median of 5% (±6% MAD [median absolute deviation]). The availability of standing trees was greatly reduced in some forests, being as low as <100 stems ≥5 cm dbh per ha in some of the most degraded forests (as opposed to >1,000 in some of the least degraded forests, and a mean stem density of 849 ±89 SE). Losses were particularly severe in the lowland coastal forests (mean across forests 20% ±28% SD; median 8% ±8% MAD), which are in direct vicinity of Dar es Salaam, a major centre of demand. The statistics for larger trees only were similar (Notes S1).

While the above statistics represent tree cutting over several years (the lifetime of a stump), the density of recent stumps can be seen as indicative of offtake rates at a given time (with a recent stump generally being 6 months or maximally 1 year old). On average (among forests) there were 3 (±0.74 SE) recent stumps >15 cm dbh per ha between 1996 and 2010. If logging rates were thus 3-6 trees per ha and year, then some 2.2-4.3 million trees >15 cm dbh would have been felled annually across the forest reserves in the study area (here restricted to ~7,200 km^2 with tree cover ≥50% according to GFW). Using a very simple above-ground tree biomass function (Chave et al., 2001; FAO, 2011) (which does not assume any knowledge of species or stand-level wood densities) this would be equivalent to a gross carbon loss of 0.41-0.82 TgC yr^{-1} if the cut trees were 20 cm dbh. However, establishing above-ground carbon is extremely challenging without detailed dbh measurements and wood density estimates. In addition, recent tree cutting was highly spatially and temporally clustered. While our data thus did not allow for a robust quantification of annual carbon losses between 1996-2010, they did however indicate that losses were substantial. In addition, there was evidence for an increase in cutting rates over the 14 years covered by the data – from less than one tree per ha and year (approximately) pre 2000 (0.4 ±0.36 SE), to around three trees per ha and year between 2000-2005 (3.3 ±1 SE), and c. four trees per ha and year post 2005 (4 ±1.2 SE). Out of 16 forests that have been visited twice (in ~2004 and ~2010) 13 had a greater density (and 14 a larger percentage) of recently cut trees in 2010 (Figure S1).

A subset of transects (n=45 covering 18.75 ha in the coastal forests; Ahrends et al., 2010) with more detailed assessments allowed for the computation of above-ground tree biomass based on exact dbh and species or genus level wood specific gravity (extracted from Chave et al. (2009)). Following equation 7 from Chave et al. (2014) and assuming a carbon fraction of dry matter of 0.5 we estimate that the area lost 8.9 MgC per ha due to cutting (over the lifetime of a stump), and 1.1 MgC in the year of the survey (2004/05). Reducing the data to the type of information that would be available with the simpler counting methodology (and assuming that poles

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measure 10 cm dbh and trees 20 cm dbh) we calculate a loss of 8.1 MgC per ha using Chave et al. (2001). Figures for standing carbon are 28.4 and 35.3 MgC per ha, respectively. Thus, (1) the area lost a significant amount of carbon of standing carbon due to cutting (24% over the lifetime of a stump, and 4% in the survey year, which was characterised by a logging boom (Milledge et al., 2007)); and (2) while the simple rapid counting methodology can provide rough carbon estimates, more detailed dbh measurements and the inclusion of at least stand-level averages for wood specific gravity will considerably enhance the accuracy of these estimates.

Comparison with remotely-sensed data datasets

There was broad agreement between the spatial patterns of tree (cover) losses recorded in the field and by GFW. However, as one would expect, more subtle degradation was not picked up by this dataset focusing on complete tree cover loss in ~28×28 m cells. GFW reported tree cover losses for only 20% of the transects that recorded new tree cutting between 2000 and 2005. The larger the proportion of cut trees the more often GFW detected loss (Table 1). A very similar picture emerged when looking at a lower dbh threshold of ≥5 cm dbh (Table S6).

To illustrate this with specific examples, Figure 2 shows a comparison of ground data and remotely-sensed data for three coastal reserves visited in 2004. While GFW detected some canopy losses between 2000 and 2005 (affecting 2% of the area with ≥50% canopy cover in 2000), degradation on the ground was already severe (with a mean of 11 ±7 SD recently cut trees ≥5 cm dbh, and 10 ±7 SD charcoal pits per ha). GFW record large losses from these areas in the following years (26% of the area with ≥50% canopy cover in 2000), confirming the early warning signals provided by the ground data. Indeed, a field survey in 2016 estimated that, since 2004, the density of trees in these areas had halved, with timber trees densities having dropped three-fold, and above-ground carbon being reduced by 40% (Ahrends et al., 2020). In one of the reserves (Vikindu) trees had almost entirely disappeared by 2016 (Fig. 2l), and the site has since been degazetted for agricultural clearing. The GFW data did not reflect Vikindu's severe state of degradation in 2004 (when much of the natural vegetation had been replaced by *Eucalyptus*, and widespread logging and charcoal production was occurring), nor the disappearance of much of the remaining forest by 2016. Less than 1% tree cover loss was detected by GFW between 2000 and 2005, and 'only' another 15% loss between 2006 and 2018 (1% and 18% of tree cover ≥50%, respectively).

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The radar-based maps on the other hand did detect subtle changes in forest condition. MN18 classed at least one pixel as either degraded or deforested in 81% of transects that recorded losses between 2007 and 2010, whereas GFW recorded losses for less than a third of these transects (Tables 2 and S7). As above, the larger the percentage of cut trees the more often losses were detected from space. The field data did not allow for a robust quantification of specificity (false positive rate) of either dataset; there were only three transects from the 2007-2010 period that recorded no losses at all (recent and old), and both GFW and MN18 recorded losses for one of these transects. The losses may well have occurred after the ground data were collected (mostly 2009), and/or may not have taken the form of tree cutting.

Overall, MN18 and GFW recorded similar amounts of deforestation (187 and 198 km^2, respectively) between 2007 and 2010 (data aggregated to 100 m resolution, and masked to 9,565 km^2 in forest reserves for which there was radar data). Aggregated to the scale of individual reserves (n=143), the two datasets provided moderately correlated estimates of percentages of area deforested (Pearson's R=0.51). Assessing both deforestation and degradation, MN18 reported an additional 727 km^2 of degradation. While some reserves experienced both deforestation and degradation, the degradation data did not correlate with the deforestation data, and instead highlighted a different set of reserves as particularly impacted.

Modelled predictions of resource harvesting

Forest resource extraction increased steeply with accessibility and proximity to centres of demand (Figures S2-S4). Particularly in the case of charcoal production, and to some extent in the case of tree cutting, models that only considered local factors such as population density and management type performed less well than models that included predictors representative of city distance and wider population pressure (with a correlation [R] between predictions and test data under 10-fold cross validation of 0.57 as opposed to 0.75 in the case of charcoal burning, and 0.62 versus 0.68 in the case of tree cutting; Table S4). Protected area management explained some variation (Tables S4-S5), with harvesting being highest in unreserved areas. However, it is important to note that the reserve categories conflate a range of factors, e.g. all productive reserves analysed here were situated at Tanzania's easily accessible coast. In addition, sample sizes were unequal (e.g. there were over 400 transects for 54 government forest reserves, and only 27 transects for 13 reserves on village land). Management on its own explained comparatively little variation (with cross-validation correlations of 0.39-0.56), which

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will in part be due to the data inadequacy mentioned above, and in part due to the overriding influence of demand and accessibility. For more details see Figure S5.

The relative importance of predictors differed for the different types of disturbances. Spatial patterns in tree cutting were almost entirely explained by urban population pressure (a distance decay function of population density; Table S1), with additional variation accounted for by distances to Dar es Salaam, roads, major cities, and steepness of terrain. Patterns in charcoal production were also mainly related to distance to Dar es Salaam and population pressure. Pole cutting, on the other hand, was best explained by a multitude of factors, including management, distances to Dar es Salaam, roads and cities, and local population density (Table S5). In interpreting the relative importance of predictors, it is important to note covariation and a degree of inter-exchangeability between them (Table S2). For instance, dropping population pressure from the full model only had a moderate effect on model performance as long as population size and city distance where still present. However, overall there was a notable difference between tree cutting and charcoal production on the one hand (almost entirely explained by variables related to accessibility from urban centres), and pole cutting on the other hand where local population density and management played a greater role in explaining the variation.

All final models performed reasonably well, achieving ten-fold cross validation correlations between 0.68-0.78 (Table S4). When setting aside 20% of the reserves as test data it was generally possible to predict the top three most degraded forests from the rest of the data.

In order to broadly investigate whether the model for tree harvesting (>15 cm dbh) was able to indicate areas under future threat, we extrapolated the model to ~2020 and compared the predictions to tree cover losses recorded by GFW between 2000 and 2018 (Fig. 3) and local reports (see below). There was general agreement between the areas predicted to face high levels of cutting by ~2020 and tree cover loss detected by GFW (Fig. 3). Obvious differences arose in areas managed as rotational plantations, where GFW detected large losses while the model predicted low impacts (Fig. 3a). For instance, Sao Hill southwest of Iringa has lost a lot of tree cover due to plantation rotation, but according to local reports the non-plantation natural forest is not impacted by degradation (BirdLife International, 2013). In several other areas the model predicted high levels of tree cutting and GFW did not report major losses; here the modelled predictions were generally confirmed by local reports suggesting that degradation

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has occurred, but may not (yet) have manifested as complete tree cover loss at the Landsat pixel scale. For example, Chome, Kwizu and Chambogo Forest Reserves in the Pare Mountains, Kisimagonja in the West Usambara Mountains, and Nianganje in the Udzungwa Mountains (Fig. 3b) are all reported to have been extensively degraded (BirdLife International, 2020; BirdLife International, 2020; Gereau et al., 2014; Makero and Malimbwi, 2012). Moderate levels of disturbance have also been reported for Uluguru and Mkingu Nature Reserves (Gereau et al., 2014). However, it is important to note that all of these reports are qualitative and terms such as 'extensively degraded' or 'managed well' are likely to be used in different ways across these reports. In addition, while GFW measure complete tree cover loss in 28 m pixel the model predicts tree harvesting pressure (not clear felling). Thus, the GFW data cannot be used to validate the model predictions and *vice versa*.

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Discussion

Here we presented a tested protocol for rapid quantitative assessments of degradation in the field, and we compared data collected with this method in Tanzanian forests with optical and radar-based remotely-sensed datasets. Covering over 600 ha our field data allowed for one of the first large-scale independent tests of these spatial datasets in southern Africa. Radar-based maps (McNicol et al., 2018) appeared to perform well, with even low levels of tree cutting generally coinciding with the detection of biomass loss. However, our study also suggests that there still is an important role for field data, which provided valuable additional information on the types of degradation and likely drivers. For instance, patterns in the field data implied that a major driver of forest degradation is demand for woody resources emanating from larger cities – a pattern that has also been confirmed in radar-based assessments (McNicol et al., 2018). The field data additionally allowed for a finer differentiation of the underlying processes, suggesting for example that it is specifically urban demand for timber and charocal which drives a lot of harvesting, with important consequences for where and how to target conservation interventions.

Degradation was pervasive in the study area, meaning that a focus on deforesation would severely underestimate significant losses of carbon and declines in forest quality. Indeed, the 'Global Forest Watch' data (GFW), which are commonly used in national forest inventories and conservation assessements, and which measure complete canopy loss at a 28 m spatial resolution, did not routinely detect even high levels of cutting associated with severe impacts on the ground in terms of loss of natural vegetation and carbon. This echoes findings from other studies which show that small-scale deforestation tends to be underestiamted by GFW, particularly in areas with low and/or seasonally dry woody cover (Bos et al, 2019; McNicol et al., 2018) where time-series analyses (Verbesselt et al. 2010; 2012) may perform better (Bos et al., 2019); but also in moist forest in Tanzania (Hamunyela et al., 2020) and elsewhere (Bos et al., 2018; Milodowski et al., 2017). This is not a critique of the data generated by GFW, but it serves as a reminder that in areas where smaller scale deforestation and degradation are a significant cause of carbon emission and biodiversity loss, such as southern and east Africa (Baccini et al., 2017; McNicol et al., 2018; Pearson et al., 2017; Sedano et al., 2020), it is necessary to go beyond easily accessible deforestation data and to use a combination of approaches to detect these changes.

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Whilst radar data correlated well with disturbance on the ground they cannot detect activities that have little impact on vegetative biomass - such as low levels of harvesting, collection of non-timber products, hunting, or the introduction of invasive alien species (McNicol et al., 2018; Ryan et al., 2012). Using remotely-sensed data it is also very challenging to distinguish types of disturbances; plantations *versus* natural forests; and primary vegetation *versus* the rapid secondary growth following logging (Asner et al., 2004). Here we counted degradation as 'detected' even if only one pixel in or around a transect, i.e. an area of up to ~20 ha, was classed as degraded or deforested. It is entirely possible that the removed tree(s) was not detected, and that the reported biomass loss was due to an unrelated co-incidental process or noise. Finally, given that almost all transects used in this study contained tree stumps it was not possible to robustly establish the specificity (=false positive rate) of the radar dataset with our data. In summary, whilst radar data give increasingly accurate wall-to-wall quantifications of degradation, there is still an important role for field data in aiding their interpretation, and providing an 'even earlier' warning signal in terms of subtle changes that can be detected before there is any notable impact on canopy or biomass. Similarly, early warning signals can also be provided by ground-based sensing, e.g. hemispherical photography and terrestrial LiDAR (Decuyper et al., 2018; Fournier and Hall, 2017).

Capturing the spatial patterns and types of degrading activities, particularly when they are illegal, requires surveying relatively large areas. Field-based inventories and monitoring are however frequently restricted to a small sub-sample of areas of interest (O'Connell, 2018). The framework presented here can be used for quick assessments of large areas without professional training, thereby also allowing for community participation (Danielsen et al., 2011; DeVries et al., 2016). Details can be adapted to the target system and question (but should of course be standardised to ensure comparability; for a recommended set of core measurements see the Supporting Field Protocol). In particular, we would recommend using a higher size class resolution than used here and/or detailed dbh measurements. Our models for tree cutting performed less well than those for pole cutting and charcoal burning, which is likely due to tree harvesting >15 cm dbh serving a multitude of purposes ranging from high-grade export timber to local construction and partly also charcoal production. Differentiating three to five size classes can still be done rapidly by eye, and even detailed dbh measurements are not too time consuming. Particularly if combined with the identification of main timber species, this would provide more information on likely markets and scale of operation. Such higher resolution data would also enable estimation of likely levels of sustainability of the resource extraction,

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whereby a decline in high-value species and/or larger trees are often indicators of unsustainability (Ahrends et al., 2010). In addition, more details, particularly on stem sizes, would also improve estimates of aboveground carbon (loss), which could only be crudely estimated using the simple counts. Another useful potential addition is collaborative work with socio-economists in order to capture local knowledge, and to understand whether the resource extraction leads to win-lose or lose-lose scenarios locally (Smith et al., 2019). The transects can be done as a stand-alone activity or in addition to more detailed assessments in long-term vegetation plots *(PPP team, please add reference to SEOSAW partnership paper in this issue)*, opportunistic botanical sampling or other types of surveys. Rapid transects cannot replace the depth of assessment possible in permanent plots, and large plots are also necessary for the calibration of radar (McNicol et al., 2018) as using narrow transects to relate radar to biomass is very challenging (Réjou-Méchain et al., 2014; Smith, 2018).

A key benefit of field data is that they can provide information on the type of biomass loss (e.g. charcoal, poles, planks, or agricultural clearing) and sometimes on the type and sophistication of equipment that was used, allowing insights into the likely drivers and tailoring interventions appropriately (Doggart et al., 2020). Here we showed that while pole cutting may partly be driven by local demand, activities such as tree cutting and charcoal production correlated almost entirely with distances to major cities such as Dar es Salaam. Degradation thus appears to be mainly driven by energy and timber demand emanating from larger cities and international markets, as opposed to mainly local demand (Ahrends et al., 2010) – a pattern that has been observed throughout southern Africa (McNicol et al., 2018; Sedano et al., 2020). Deforestation on the other hand is mainly driven by agriculture, highlighting the need for coordinated policy responses (Doggart et al., 2020; Hamunyela et al., 2020). It should also be noted that whilst the clear spatial patterns meant that degradation was to some extent predictable, dynamics in markets, human behaviour and policies can lead to rapid changes on the ground - such as the introduction of sesame farming in Tanzania (Brockington, 2019; Gross-Camp et al., 2019; Müller et al., 2014). Thus, although models can to some extent be used to extrapolate patterns in space and time, there is a clear need for regularly updated data (Sloan and Pelletier, 2012).

Protection on the ground has had some success in halting degradation but the type of management was less important in explaining patterns of forest condition than demand and accessibility. This suggests that any form of protection can be better than none, and putting

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land under the tenure and management of local communities might be a mutually beneficial way to reserve some of the 170,000 km^2 of forest on general land in Tanzania (Mbwambo et al., 2012), excluding rural populations from the resources their livelihoods rely upon. Tree cutting in village-owned reserves only slightly exceeded levels in protective forests and nature reserves but this was to be expected as village land forest reserves often allow sustainable extraction. The effectiveness of village participation in forest management (co-management) could not be robustly assessed because much of the data were collected when joint forest management agreements were in very early stages (Mbwambo et al., 2012).

The early warning provided by both radar and field data compared to GFW is a key advantage, because severe degradation and deforestation often follow the early stages of degradation (FAO, 2011) – a sequence we also observed here. However, in terms of (temporal) data availability, a significant advantage of GFW is that the readily processed data are freely available on an annual basis with global coverage, explaining their widespread use. This is not yet true for radar-based maps; while raw data are now freely available costs arise in the form of trained technician(s). Field surveys, if done by local surveyors, could in theory also be done at least annually. Costs associated with training local surveyors and establishing reporting processes mean that rapid field surveys will incur the greatest costs at the start (to give an example, in 2016 we spent around £30k for the survey of 10 Tanzanian forests) but subsequent investments will be considerably lower. Depending on the vegetation and the desired level of species identification the transects can almost be done at walking pace, meaning it is generally possible for a team to do at least one transect a day, and that costs arise in the form of c. 10 days' worth of salary for the surveyor team, transport, and costs for data entry. In practice, a combination of at least annual (radar-based) remote sensing, combined with rapid field surveys in at least 1-3 year intervals to better understand the drivers, may prove to be a good compromise.

Strictly speaking, the method presented here only quantifies woody resource extraction and not necessarily degradation. The latter is challenging to establish – particularly in systems where little is known about regeneration and growth rates. However, whilst systems adapted to frequent natural disturbance may be resilient to some resource extraction, the selective extraction of larger trees in old-growth forest can negatively impact ecosystem function and biodiversity (Jew et al., 2015; Tripathi et al., 2019; Yguel et al., 2019). In addition, whilst there is controversy over the role of wood products in carbon storage, the damage to the surrounding vegetation in denser forests, as well as the associated transportation and processing of the timber, tend to be associated with substantial emissions (Ingerson, 2009; Pearson et al., 2014). Resource extraction in old-growth forests thus requires careful regulation. The vast majority of extraction recorded here took place in protective (as opposed to productive) reserves, and was consequently mostly unregulated and illegal with no concomitant legal revenue benefits for Tanzania as a state (Milledge et al., 2007).

In conclusion, the consideration of degradation in global forest reporting is important - particularly in southern Africa where the area affected by degradation is likely to be double the size of the area that is deforested, and overall carbon emissions from forest degradation are likely to exceed those from deforestation (McNicol et al., 2018). We recommend to routinely use radar-based monitoring combined with, wherever possible, rapid field assessments to better understand the quality of forests and the reasons for their decline, to provide an early warning, and to allow for informed and timely policy interventions.

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Author contributions

A.A., N.D.B., M.T.B., R.M., P.J.P. and P.M.H. designed the study; A.A. and M.T.B. performed analyses with analytical advice from P.J.P., R.S., C.R. and N.D.; field data were collected by A.A., P.M., S.M., B.M., C.L., C. B., K.D., V.W., N.O., A.R.M., K.P., A.M., T.J., E.T.J., and H.B.. All authors discussed the results and commented on the manuscript.

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Tables

Trees >15 cm dbh recently cut (2000-2005)	N transects	N transects with ≥1 pixel recording tree cover loss between 2000-2005 according to GFW		
		100 m buffer	50 m buffer	28 m buffer
>0%	88	31 (35%)	23 (26%)	18 (20%)
≥1%	55	20 (36%)	15 (27%)	11 (20%)
≥5%	18	12 (67%)	9 (50%)	5 (28%)
≥10%	9	7 (78%)	5 (56%)	2 (22%)
≥25%	2	2 (100%)	1 (50%)	1 (50%)
≥50%	1	1 (100%)	1 (100%)	1 (100%)

Table 1. Comparison of on-the-ground losses and tree cover losses recorded by Hansen *et al.* (2013; GFW) between 2000 and 2005 (with a spatial resolution of ~28 m).

Trees >15 cm dbh recently cut (2007-2010)	N transects	N transects ≥1 pixel tree cover loss 2007-2010 (GFW)	N transects	N transects ≥1 pixel deforestation/degradation 2007-2010 (MN18)		
				Defores-tation	Degradation	Deforestation or degradation
>0%	52	15 (29%)	42	6 (14%)	33 (79%)	34 (81%)
≥1%	30	7 (23%)	23	4 (17%)	21 (91%)	21 (91%)
≥5%	6	1 (17%)	3	1 (33%)	3 (100%)	3 (100%)
≥10%	3	1 (33%)	1	1 (100%)	1 (100%)	1 (100%)
≥25%	1	1 (100%)	0	*Na*	*Na*	*Na*

Table 2. Comparison of on-the-ground losses, tree cover losses recorded by Hansen *et al.* (2013; GFW) and deforestation and degradation recorded by McNicol *et al.* (2018; MN118) for 2007-2010 within a 100 m buffer around transects. The numbers of transects differ because of gaps in the data generated by MN18.

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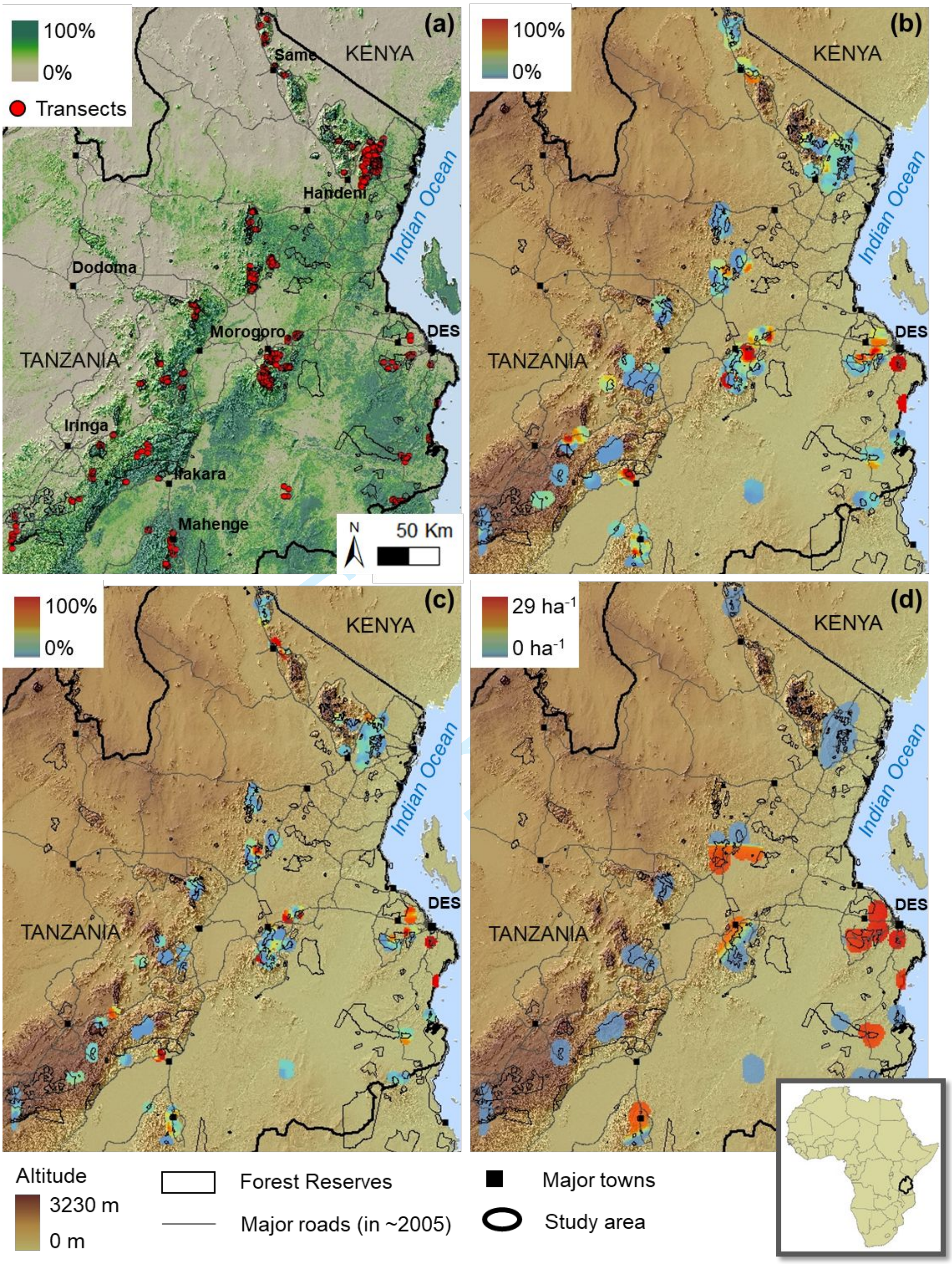
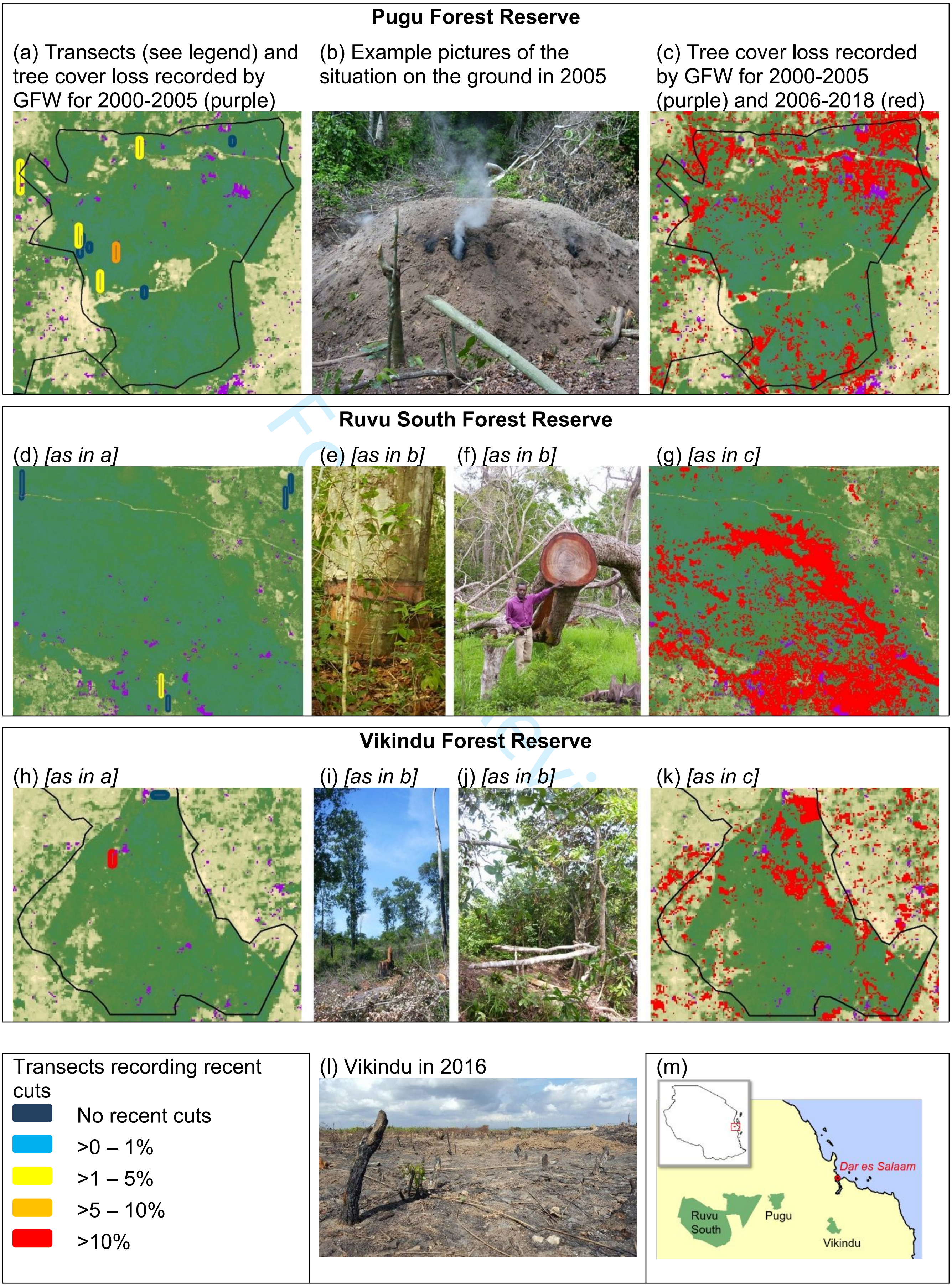


Figure 1. Transects and field data. Panel (a) shows the location of the disturbance transects and percent tree cover according to Hansen et al. (2013). Note that this includes tree crops, e.g. cashew nut, explaining the large areas of tree cover outside reserves (denoted by black lines). Panels b-d show kernel density maps of different forest condition measures: percentage of poles cut (≥5-15 cm dbh) (b), larger trees cut (>15 cm dbh) (c), and the density of charcoal kilns (d). The bold black line indicate the area to which models were extrapolated (see overview map; in panels a-d only partly visible).



Pugu Forest Reserve
(a) Transects (see legend) and tree cover loss recorded by GFW for 2000-2005 (purple)
(b) Example pictures of the situation on the ground in 2005
(c) Tree cover loss recorded by GFW for 2000-2005 (purple) and 2006-2018 (red)
Ruvu South Forest Reserve
(d) [as in a]
(e) [as in b]
(f) [as in b]
(g) [as in c]
Vikindu Forest Reserve
(h) [as in a]
(i) [as in b]
(j) [as in b]
(k) [as in c]
Transects recording recent cuts
No recent cuts
>0 – 1%
>1 – 5%
>5 – 10%
>10%
(l) Vikindu in 2016
(m)
Dar es Salaam
Ruvu South
Pugu
Vikindu

Figure 2. Comparison of ground data collected in 2004 and maps generated by Hansen et al. (2013; GFW) for three coastal reserves: Pugu (a-c), Ruvu South (d-g), and Vikindu (h-l). Left panels a, d and h show the location of transects (colours reflect rates of new cutting). The dark green background is tree cover ≥50% in 2000 reported by GFW. Black lines are reserve outlines. Purple areas have experienced tree cover loss between 2000-2005 according to GFW. Much of the degradation recorded on the ground (for examples see pictures b, e, f, i, j taken in 2004) is not reflected in the remotely sensed deforestation maps. The GFW maps register larger tree cover losses in subsequent years (2006-2018; right panels c, g and k), confirming the early warning signal set by the ground data. Picture l shows Vikindu in 2016.

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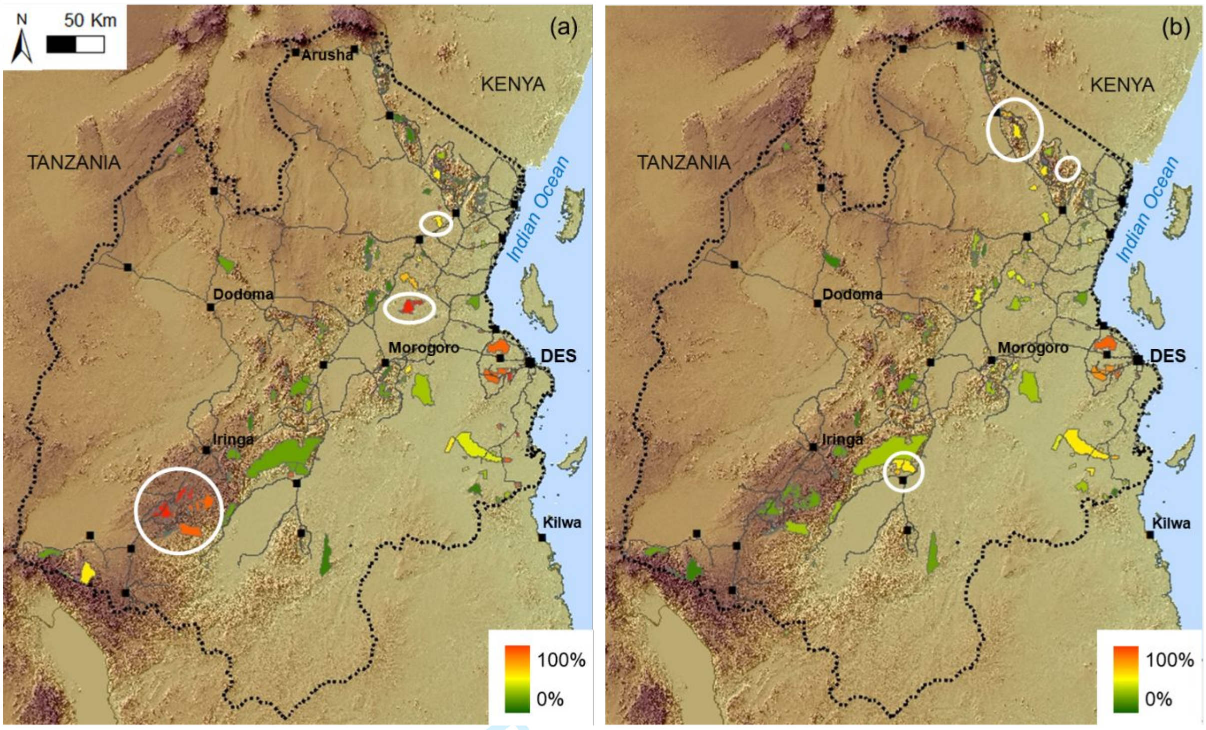

Figure 3. Comparison of tree cover losses according to Hansen et al. (2013; GFW) and modelled prediction of tree cutting by 2020. Note that the legends are not direclty comparible. Panel (a) shows the percent area (in forest reserves) affected by tree cover losses between 2000 and 2018 according to GFW. Panel (b) shows the mean predicted percent of trees (≥15 cm dbh) cut. The model achieved a ten-fold cross-validation correlation between actual and fitted values of 0.68 (± 0.04 SE); for details on model parameteristion and performance see Tables S4-5 and Figure S2. The general patterns between modelled and actual tree (cover) losses appear similar. Circled areas in (a) contain reserves managed as plantations, where tree cover losses are larger than the model would suggest. Circled areas in (b) experienced less detectable tree cover losses than the model suggests but are highly degraded according to local reports.

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