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Improved estimates of mangrove cover and change reveal catastrophic deforestation in Myanmar

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Abstract

Mangroves are one of the world's most threatened ecosystems, and Myanmar is regarded as the current mangrove deforestation hotspot globally. Here, we use multi-sensor satellite data and Intensity Analysis to quantify and explain patterns of net and gross mangrove cover change (loss, gain, persistence) for the 1996–2016 period across all of Myanmar. Net national mangrove cover declined by 52% over 20 years, with annual net loss rates of 3.60%–3.87%. Gross mangrove deforestation was more profound: 63% of the 1996 mangrove extent had been temporarily or permanently converted by 2016. Rice, oil palm, and rubber expansion accounted for most conversion; however, our analysis revealed targeted systematic transitions of mangroves to water (presumably aquaculture) and built-up areas indicated emerging threats for mangroves from those land uses. Restoration programmes facilitated mangrove gains and represent a critical area for investment alongside protection. This study demonstrates the importance of multi-sensor satellite data for national-level mangrove change assessments, along with gross land cover transition analyses to assess landscape dynamics as well as prioritise threats and interventions in an effort to develop holistic strategies that aim to conserve important habitats.

1. Introduction

Mangroves account for only 0.7% of the Earth's tropical forest area (Giri *et al* 2011), but are among the world's most productive and important ecosystems that provide a wide range of ecological and socio-economic benefits to human society (Alongi 2002, Barbier 2007). Mangroves have long been recognised as one of the world's most threatened tropical biomes (Field *et al* 1998, Polidoro *et al* 2010), with previous research estimating at least 35% mangrove area loss between 1980 and 2000 (Valiela *et al* 2001). Southeast Asia has the highest mangrove biodiversity globally (Polidoro *et al* 2010) and the highest proportion of global mangrove extent (32.2%–33.8%) (Thomas *et al* 2017, Bunting *et al* 2018), of which have declined at an average rate of 0.18% annually between 2000 and 2012 based on recent estimates, with replacement land uses (e.g. rice, oil palm, and aquaculture) varying across countries (Richards and Friess 2015).

Accurate estimates of land cover and change dynamics are of paramount importance to provide a robust foundation to inform management and conservation strategies, and Myanmar has been a focal area of this advancement given its expansive mangroves, high societal dependence on them, and the expected intensification of pressures to convert them over the next decade (Webb *et al* 2012, Lim *et al* 2017, Prescott *et al* 2017). A recent and revised Landsat-derived estimate of mangrove cover and change for Myanmar highlighted a growing mangrove deforestation crisis, and demonstrated the need to develop ground-up datasets and avoid sub-setting global datasets for national-level mangrove estimates (Estoque et al 2018). Other studies have demonstrated the importance of reporting gross land cover statistics when evaluating change dynamics, including mangroves (Thomas et al 2017, Estoque et al 2018, Gaw et al 2018, De Alban et al 2019). This is because gross land cover change estimates provide essential information on transitions among land cover classes unavailable through net change studies, leading to a more robust analysis of the drivers of land cover change (Pontius et al 2004, Aldwaik and Pontius 2012), which is especially important for relatively dynamic mangrove communities since they are amenable to rapid deforestation (loss) but can also rapidly regenerate (gain) when biophysical conditions are appropriate (Lewis 2005, Loon et al 2016).

Here, we report improved estimates for mangrove cover and change for all of Myanmar over a 20-year period (1996–2016; subdivided into two time-intervals, where I1 is 1996–2007 and I2 is 2007–2016, which were defined by the availability of satellite imagery). Our estimates incorporate multi-sensor satellite data to improve the detection of various land cover types, especially oil palm and rubber plantations in Myanmar (see De Alban et al 2018), thereby allowing us to quantify gross land cover transitions, and particularly derive spatially explicit estimates of mangrove cover transitions. We report that mangroves were more expansive and experienced significantly faster rates of loss than previously recognised, indicating a major deforestation crisis. We use Intensity Analysis to determine linkages between patterns and processes of mangrove change by identifying systematic transitions, which identified emerging proximate causes. We supplement this with an assessment of underlying drivers of mangrove cover change through extensive literature review and field observations.

2. Methods

2.1. Data

We mapped land cover for the entire of Myanmar and then analysed mangrove cover change (covering six coastal sub-national regions/states) over a 20-year period at three time-points (i.e. 1996, 2007, 2016). The analysis combined Landsat and L-band Synthetic Aperture Radar (SAR) data to take advantage of the benefits that the synergy of these datasets offer, such as for monitoring land cover change and threats to biodiversity (De Alban et al 2018, Schulte to Bühne and Pettorelli 2018). For optical data, we used Landsat-5 Thematic Mapper (TM; for 1996 and 2007) and Landsat-8 Operational Land Imager (OLI; for 2016) 30 m calibrated top-of-atmosphere reflectance products. For SAR data, we used Japan Earth Resources Satellite (JERS-1 SAR for 1996) and the Advanced Land Observing Satellite Phased Array L-band Synthetic Aperture Radar (ALOS/PALSAR-1 for 2007 and ALOS-2/PALSAR-2 for 2016) 25 m mosaic data. In addition, we used the 30 m Shuttle Radar Topography Mission (SRTM) digital elevation model (Farr et al 2007) in our image data stacks as ancillary data to further improve discrimination of land cover types and classification accuracies. Landsat, PALSAR, and SRTM were accessed through the data catalogue of Google Earth Engine (GEE; https://earthengine.google.com) (Gorelick et al 2017), while the JERS-1 mosaics were downloaded from the Japan Aerospace Exploration Agency's ALOS Research and Application Project (http://eorc.jaxa.jp/ALOS/en/palsar_fnf/fnf_index.htm), which were then uploaded as image assets in GEE.

We used reference land cover data from three sources: ground-truth information collected in the field, crowdsourcing platforms, and from visual interpretation of historical high-resolution Google Earth imagery using the Open Foris Collect Earth system (http://openforis.org/tools/collect-earth.html) (Bey et al 2016). We defined our land cover classification scheme (table S1.1 in SM 1.3 is available online at stacks.iop.org/ERL/15/034034/mmedia) from these sources, from which we then conducted a land cover assessment to delineate regions-of-interest (ROI) polygons for training and testing the classification algorithm.

2.2. Land cover classification and change analysis

Our overall workflow consisted of five stages: image pre-processing, delineation of ROI, image classification, accuracy assessment, and change analysis (SM 1.1).

The Landsat and L-band SAR images were pre-processed using the GEE platform. For Landsat data, we generated the best-available-pixel Landsat image composites (adopting the image compositing script in De Alban et al 2018) for each of the three time-points, which extracted the best available observations from the median of multiple Landsat images within a two-year period (e.g. the 1996 image composite was drawn from Landsat images from 1996 to 1997). In addition to the standard reflectance bands (i.e. visible, near-infrared, thermal, shortwave-infrared), we calculated six indices including the Enhanced Built-up and Bareness Index, Enhanced Vegetation Index, Land Surface Water Index, Normalised Difference Tillage Index, Normalised Difference Vegetation Index, and Soil-Adjusted Total Vegetation Index (SM 1.2). For the L-band SAR data, using only the HH-polarisation channel, we first applied the Refined Lee filter to reduce the effects of speckle apparent in raw SAR imagery (Lee et al 1994), and then converted the filtered images to normalised radar cross-sections (SM 1.2). We then resampled the SAR images to 30 m spatial resolution to match the Landsat and DEM layers. Finally, we derived eight second-order texture measures (i.e. grey-level co-occurrence matrices) including angular second moment, contrast, correlation, dissimilarity, entropy, inverse difference moment, mean, and variance (Haralick *et al* 1973, Conners *et al* 1984).

For delineating ROIs in Collect Earth, we first organised all reference land cover data points, and from this combined collection of data points we subsequently generated one-hectare square ROI polygons. We then assessed the land cover type (based on table S1.1) of each ROI polygon for each of the three time-points both using a pre-designed land cover survey form to streamline the land cover assessment process, and a land cover interpretation key, which consisted of snapshot images of different land cover types and their corresponding time-series spectral plots, to guide our visual land cover assessment of each individual polygon within the Collect Earth system (SM 1.3).

For image classification in GEE, we first created image stacks at each time-point consisting of 13 Landsat bands/indices, nine SAR channel/textures, and one elevation layer, totalling 23 image layers. We clipped all layers of the final image stacks using a bounding box (91°–102° E longitude; 8°–30° N latitude) and masked out pixels beyond a 5 km buffer from the coastline; the reference land cover data were also collected across the extent of this bounding box. We then partitioned all the ROIs into training and testing polygons (table S1.2 in SM 1.3), and after which we selected a subset of all pixels within each of the training and testing polygons as training and testing pixels, respectively (table S1.3 in SM 1.4). We then employed the Random Forest machine learning classifier (Breiman 2001) to implement supervised land cover classification using the selected training pixels and image stacks corresponding to each of the three time-points.

For accuracy assessments, we used two independent approaches. First, we followed the good practice recommendations for assessing the accuracies of land cover and change maps (Olofsson *et al* 2014) (SM 1.5). We used the Area Estimation & Accuracy Assessment ($AREA^2$) in GEE, which provides the tools for designing sampling strategies and calculating accuracy estimates with confidence intervals (https://area2.readthedocs.io/en/latest/index.html) (Olofsson *et al* 2014), complemented by manual calculations. We note here that we manually calculated the accuracy assessments for both land cover maps and mangrove change maps since $AREA^2$ implemented a rounding up of values in the error matrices and did not calculate confidence intervals for producer's accuracies. Importantly, the manually calculated accuracy assessments corroborated the accuracies estimated from $AREA^2$ tool, with very minor differences observed in the reported standard errors. We adopted a stratified random sampling design for both the classified land cover maps per time-point, and the mangrove change maps per time-interval (Cochran 1977, Olofsson *et al* 2014) (SM 1.5). We evaluated the accuracies of the classified land cover maps per time-point using the selected testing pixels based on a proportional allocation sampling strategy and calculated the standard accuracy assessment metrics (i.e. error matrix, overall accuracy, user's and producer's accuracies) (SM 1.5.a). We also evaluated the accuracies of the mangrove change maps per time-interval, specifically for 18 transitions (i.e. one class of mangrove persistence, eight classes of mangrove loss, eight classes of mangrove gain, and one class of non-mangrove persistence), using testing pixels based on an equal allocation sampling strategy and calculated the same standard accuracy assessment metrics (SM 1.5.b). For the accuracy assessment of mangrove change maps, given that mangroves were a 'rare' category in our land cover maps (only 2% of Myanmar's total land area), mangrove change transitions, which comprised a subset of mangrove cover were even 'rarer' in the mangrove change maps. Hence, we decided to adopt an equal allocation sampling approach to avoid under-representation of 'rare' mangrove transitions for accuracy assessments (see SM 1.5.b and table S1.5). Second, we used the quantification of hypothetical map errors from the Intensity Analysis framework (Aldwaik and Pontius 2012, 2013) for evaluating the accuracies of change maps (i.e. to gauge whether the changes are due to real change or map error) (SM 1.6.b).

For change analysis, we generated transition matrices by calculating the area of all land cover transitions within each of the six coastal sub-national administrative units (states/regions) of Myanmar per time-interval, and subsequently analysed both net and gross land cover change (SM 1.6). For net land cover change, we calculated the total areal extent of mangrove cover per time-point for each sub-national unit, and then subsequently calculated net area of mangrove cover change again for each sub-national unit per time-interval. Annual rates of mangrove cover change per sub-national administrative unit were then calculated (using equation (7) in Puyravaud 2003) (SM 1.6.a). For gross land cover change, we quantified gross mangrove persistence (or the area of unchanged mangrove pixels), gross mangrove loss, and gross mangrove gain. By definition, a transition matrix for a given time-interval presents gross persistence (diagonals), gross gains and losses (off-diagonals), and net extents (row and column totals) for all land cover classes. We note here that we were unable, however, to calculate adjusted area estimates as recommended by Olofsson *et al* (2014) for the following reasons. First, our accuracy assessments were based on both image and reference datasets that encompassed the larger extent of the bounding box, and not just within Myanmar's coastal sub-national mangrove regions/states; hence, making the area adjustment applicable only for adjusting the area proportions in that larger extent. Second, we were also limited by practical considerations since calculating adjusted areas would necessitate accuracy assessments for each of the six coastal regions/states per time-point. Finally, since we implemented an equal allocation sampling strategy for assessing the accuracy of the mangrove change maps, the trade-off according to Olofsson *et al* (2014) was that the use of an equal allocation strategy 'is not optimised for estimating area' (see SM 2.3).

To analyse the processes associated with mangrove cover change, transition matrices were analysed within the Intensity Analysis framework using both the *intensity.analysis* (Pontius and Khallaghi 2019) and *raster* (Hijmans *et al* 2019) packages in R v.3.4 (https://r-project.org) (R Core Team 2016) and a Microsoft Excel Macro spreadsheet (https://sites.google.com/site/intensityanalysis) (Aldwaik and Pontius 2012) (SM 1.7). Intensity Analysis has been extensively applied to detect systematic transitions and dominant signals of land change, thus providing a basis for identifying the proximate causes and underlying drivers of change (Pontius *et al* 2004, Braimoh 2006, Aldwaik and Pontius 2012, Huang *et al* 2012, Teixeira *et al* 2014, De Alban *et al* 2019). Systematic transitions are a two-sided land cover change relationship, and can be targeted or avoided in nature (Aldwaik and Pontius 2012). For a targeted systematic mangrove loss transition, the loss of mangrove targets a destination land cover type, and reciprocally that land cover type targets mangrove for its gain. For a targeted systematic mangrove gain transition, the gain of mangrove targets a particular source land cover type, and the loss of that source targets the gain of mangrove. For an avoided systematic transition, the opposite occurs: the loss of mangrove avoids a particular destination land cover type (and vice versa), and the gain of mangrove avoids a particular source land cover type (and vice versa). Using this framework, proximate causes of mangrove cover change are destination and source land cover types that are associated with (a) the largest areas of mangrove cover change, or (b) systematic transitions. We explored the underlying drivers of mangrove cover change at the relevant international/national/sub-national scales using available literature and field observations (especially MMT).

All map figures were designed in QGIS v.2.18 (https://qgis.org/en/site/) (QGIS Development Team 2018), and all visualisation plots were constructed in R, mainly using the *tidyverse* (Wickham and RStudio 2017), *plyr* (Wickham 2016), *readxl* (Wickham *et al* 2019), and *egg* (Auguie 2018) packages.

3. Results

3.1. Accuracy assessments

High overall accuracies and low uncertainties were obtained for the land cover classification maps (85.6%–95.6%; table S2.3). These accuracies align with previous studies showing improved detection and discrimination of various land cover types (e.g. oil palm, rubber, agroforests) using multi-sensor data over optical satellite data only (Torbick *et al* 2016, De Alban *et al* 2018, Schulte to Bühne and Pettorelli 2018, Yang *et al* 2018), and lend high confidence to our estimates. High overall accuracies and low uncertainties were similarly obtained for the mangrove change maps (94.4%–97.1% for detailed transitions, table S2.8; 95.2%–97.4% for aggregated transitions, table S2.11); however, low user's and producer's accuracies were obtained for many loss and gain transitions, except mangrove and non-mangrove persistence (SM 2.2.a and SM 2.2.b). Hence, for the subsequent change analysis, we relied on the estimation of hypothesised errors from the Intensity Analysis framework, which provided an independent accuracy assessment of the mangrove change maps (SM 2.5.c). Intensity Analysis allowed the identification of systematic mangrove transitions, and the evaluation of non-systematic mangrove change transitions that were due to real changes and not map errors (SM 2.5.c).

3.2. Mangrove cover and proximate causes of change

Across all six states/regions and collectively, our estimates indicate (1) a greater mangrove extent historically, and (2) faster deforestation rates, than previous studies. We estimated a total of 13 233 km^2 of mangroves across Myanmar in 1996, with more than 90% occurring in the regions/states of Ayeyarwady, Rakhine, and Tanintharyi (figure 1; table 1). Total net mangrove cover declined by 52% over 20 years, from 13 233 km^2 in 1996 to 8907 km^2 in 2007 to 6287 km^2 in 2016. National net mangrove loss was 65% higher in I1 than I2 (4326 km^2 versus 2621 km^2, respectively). Regions/states with low mangrove cover extents (Bago, Mon, Yangon) fared poorly, with each administrative unit losing more than 80% of their 1996 extent.

Rice paddy expansion was the most important proximate cause of mangrove loss over the two time-intervals (2962 km^2 in I1 and 2439 km^2 in I2; i.e. 47% and 68% of gross mangrove losses, respectively) (figure 2). Oil palm expansion accounted for 1261 km^2 (20%) in I1 and 530 km^2 (15%) in I2 of gross mangrove losses, with regions of oil palm conversion in Tanintharyi and Ayeyarwady (figures 3–4; tables S2.12 and S2.16 in SM1.3). Rubber and shrub/orchard consisted a total of 395 km^2 (6%) and 875 km^2 (14%) of total gross mangrove loss in I1. Water body (presumably aquaculture, at least partially) was a minor contributor to total mangrove conversion in both time-intervals (figure 2).

Transition-level Intensity Analysis revealed 18 (I1) and 14 (I2) targeted systematic mangrove loss transitions (table 2). Out of 12 possible transition occurrences (6 regions/states × 2 time-intervals) for each mangrove loss type (e.g. MNG-WTR, MNG-OPM, etc), targeted systematic mangrove losses occurred most frequently for oil palm plantations (11 occurrences), water bodies (7), and built-up areas (5). This means that although the total area of mangrove conversion into oil palm, water bodies, and built-up areas

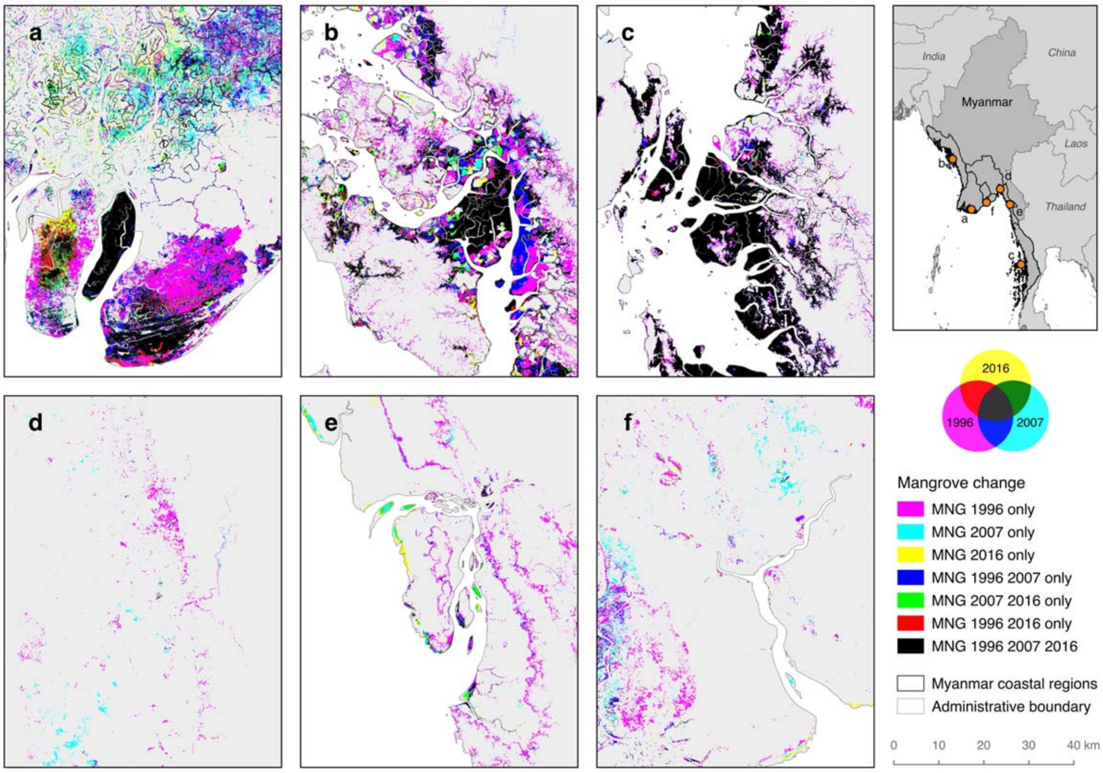

Figure 1. Gross mangrove change over three time-periods (1996, 2007, 2016) in selected sites (orange points) within each of the coastal regions/states in Myanmar, specifically (a) Ayeyarwady Region, (b) Rakhine State, (c) Tanintharyi Region, (d) Bago Region, (e) Mon State, and (f) Yangon Region.

Table 1. Total extent of mangrove cover in 1996, 2007, and 2016 for each coastal region/state in Myanmar, including their net area mangrove cover change and calculated annual rates of mangrove cover change for each time-interval (1996–2007 and 2007–2016).

	Total extent						Net area change		Annual rate of change[a]	
	1996		2007		2016		1996–2007	2007–2016	1996–2007	2007–2016
Region / State	km^2	%	km^2	%	km^2	%	km^2	km^2	%	%
Ayeyarwady	4289	32	3315	37	2004	32	−974	−1311	−2.34%	−5.59%
Bago	237	2	173	2	19	0	−64	−154	−2.86%	−24.73%
Mon	849	6	211	2	106	2	−637	−105	−12.63%	−7.67%
Rakhine	3443	26	1780	20	1309	21	−1663	−472	−6.00%	−3.42%
Tanintharyi	4212	32	3285	37	2813	45	−927	−472	−2.26%	−1.72%
Yangon	203	2	143	2	37	1	−60	−106	−3.18%	−15.10%
Total	13 233	100	8907	100	6287	100	−4326	−2621	−3.60%	−3.87%

[a] Shows calculated annual rates of change using equation (7) in Puyravaud (2003).

accounted for only 25% and 26% of total mangrove losses in I1 and I2, respectively, the gains by those destination land cover types were dependent on mangrove conversion. In contrast, rice paddies systematically targeted mangrove loss in only four occurrences for both time-intervals (despite accounting for 47% and 68% of total mangrove losses in I1 and I2, respectively), indicating that rice paddy gained from a wide range of land cover types other than mangroves (i.e. the relationship was not reciprocal). The most common avoided systematic transition for mangrove loss was into forest (9 occurrences), followed by bare ground (5) and shrub/orchard (3) (table 2), which means that mangrove losses were not into these destination land cover classes. Thus, while the main proximate causes (based on total area converted) of mangrove loss in Myanmar were the expansion of rice, oil palm (also systematically transitioning), and rubber, systematic transitions also implicated aquaculture and urban expansion as latent proximate causes.

Total gross mangrove gains nationally were 2004 km^2 and 967 km^2 in I1 and I2, respectively. Mangrove gains were largely attributed to reversion from rice paddies, constituting 75% (1493 km^2) and 70% (674 km^2) of total mangrove gains in I1 and I2, respectively (figure 2). However, the transition was not systematic

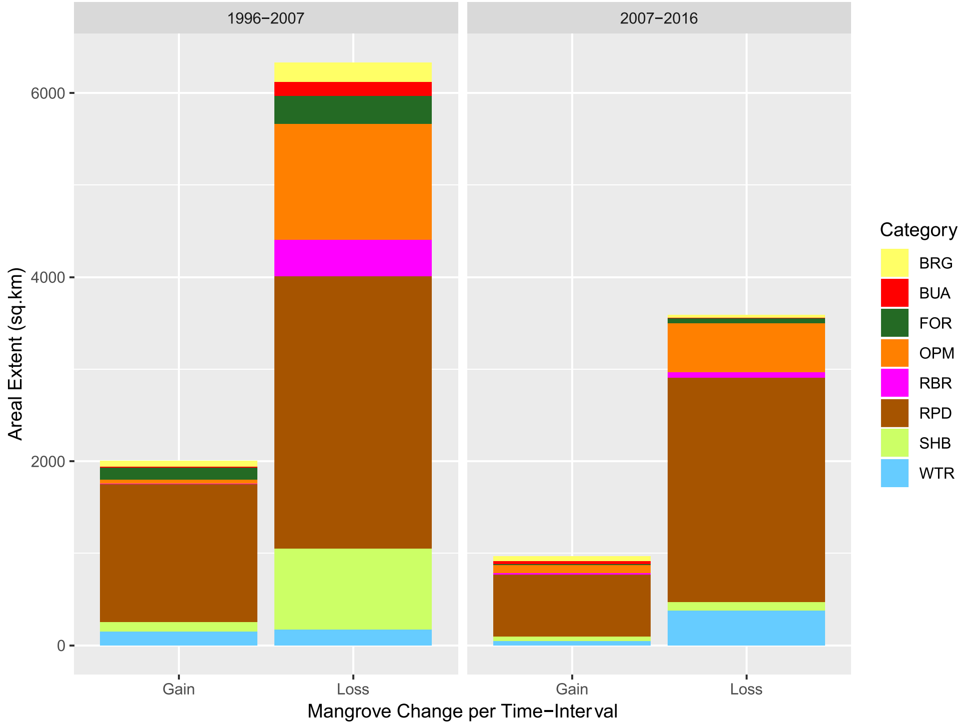

Figure 2. Areal extent of land cover categories to which mangroves lose to and gain from in each time-interval across all the six mangrove sub-national units in Myanmar.

as rice paddy transitioned into other non-mangrove destination land cover types. Rather, the most common targeted systematic mangrove gains were from water bodies (8 occurrences), oil palm (5), and bare ground (5) (table 2). The most frequent avoided systematic transitions for mangrove gain were from forest (11 occurrences) and rubber (10), with shrub/orchard (5) a distant third. Mangrove reforestation was the main proximate cause of the identified systematic transitions associated with mangrove gains. Restoration programmes occurred in abandoned agricultural land, such as rice paddies and aquaculture ponds in Ayeyarwady and Rakhine (figures 4 and 5) (Maung 2012, Aung *et al* 2013, Zöckler *et al* 2013, Veettil *et al* 2018).

Mangrove persistence, defined as area that remain unchanged during a time-interval, was 6902 km^2 in I1 (52% of 1996 area) and 5321 km^2 in I2 (60% of 2007 area). When evaluated over the entire 20-year period, persistence was only 4867 km^2 (37% of 1996 area), which means that 63% of Myanmar's mangroves were converted to another land cover type since 1996. The primary proximate cause of mangrove persistence was protection through mangrove reserves, particularly the Mein Ma Hla Kyun Wildlife Reserve (~137 km^2) in Ayeyarwady Delta, given the protection it afforded over mangroves (figure 4) (Webb *et al* 2014). A second proximate cause is accessibility: since gross change maps clearly demonstrate the nature of mangrove deforestation as occurring in the most accessible areas, regions that are less accessible contribute to mangrove persistence (figure 1).

4. Discussion

4.1. Underlying drivers of mangrove cover change

Underlying the proximate causes of mangrove loss are drivers unique to Myanmar. Rice expansion is smallholder-driven to enhance livelihoods and employment (Okamoto 2007, Matsuda 2009, Stokke *et al* 2018); interventions dating back to the 1980s include capital intensification, development of irrigation infrastructure, agricultural mechanisation, crop diversification, and improvement of agricultural management practices; and market liberalisation and reforms in 2003 further incentivised rice expansion (Okamoto 2007, Matsuda 2009, Webb *et al* 2014, Torbick *et al* 2017). Mangrove conversion to oil palm in Myanmar (Richards and Friess 2015), in contrast, was driven by large-scale agribusiness concessions, particularly targeting Tanintharyi (Connette *et al* 2016), to meet domestic and industrial demands for palm oil and achieve self-sufficiency in edible oils (Donald *et al* 2015). Rubber plantations in Myanmar increased by 140% in I1, such as in Mon and Tanintharyi where smallholder plantations were prevalent, as a result of the government's introduction of market liberalisation measures and the rise of international rubber prices (Woods 2012, Vagneron *et al* 2017). Rubber plantations are expected to further expand given the Myanmar government's plans to increase rubber acreage and production capacity, as well as the availability of suitable vacant land area in the rubber-growing regions (Vagneron *et al* 2017). The systematic transitions of mangrove losses/gains to/from water bodies

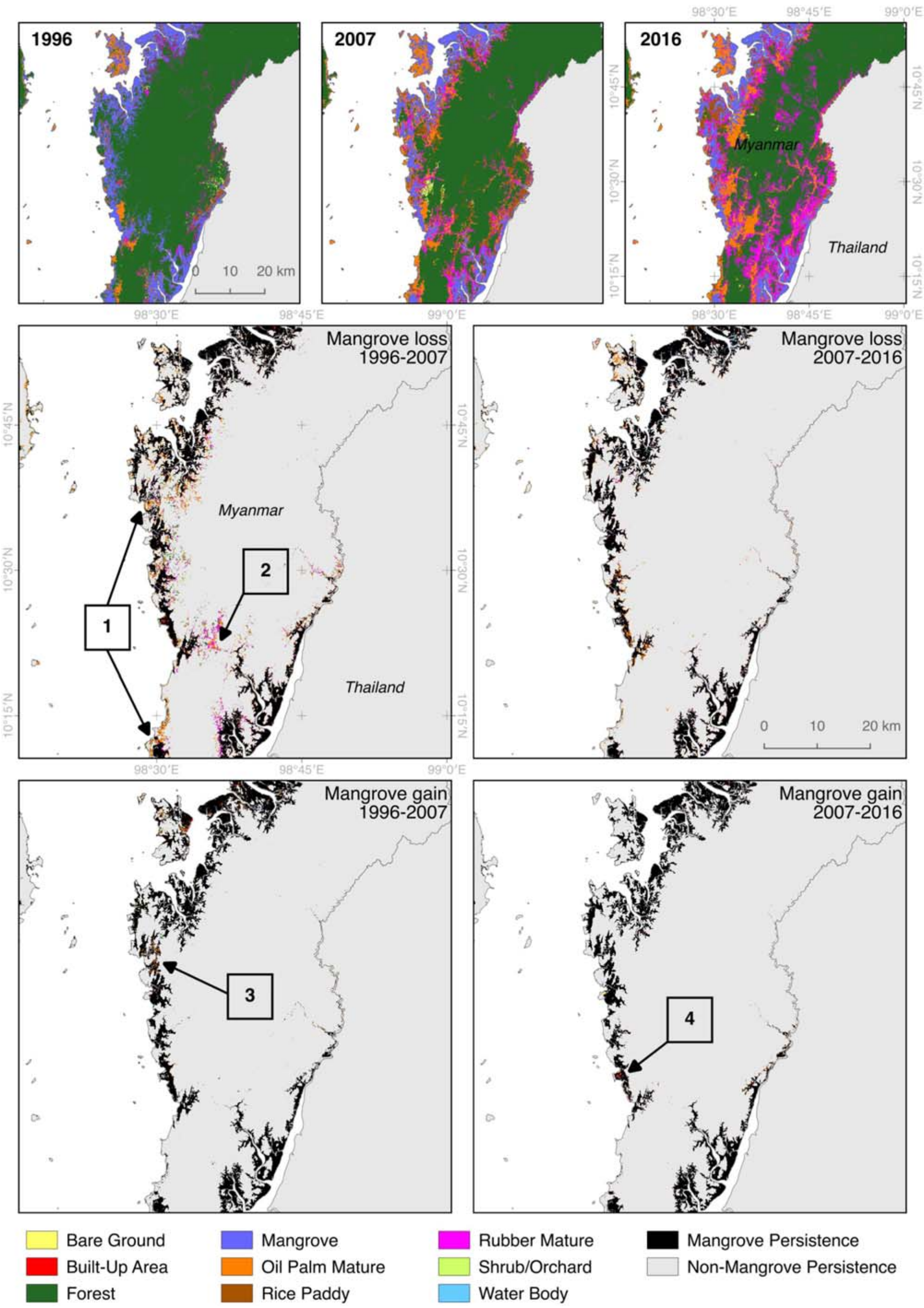

Figure 3. Land cover in 1996, 2007, 2016 (top panel) and mangrove loss and gain in 1996–2007 and 2007–2016 in Tanintharyi Region. Persistence of extensive mangrove areas can be observed such as along the coastlines of Myeik and Kawthoung Districts. Mangrove conversion into oil palm is a systematic transition that can be observed more prominently in many parts of Tanintharyi [1]. Also, mangroves were converted into rubber plantations such as in I1 [2], albeit this transition is non-systematic. Mangroves were systematically gained from rice paddy during I1 [3] and from built-up areas in both intervals [4].

suggest a potentially burgeoning threat of aquaculture development in all sub-national units, previously only speculated on by previous studies in Myanmar (Oo 2002, Giri *et al* 2008, Maung 2012, Zöckler *et al* 2013, Richards and Friess 2015, Gaw *et al* 2018, Veettil *et al* 2018). Expansion of aquaculture began in the late 1990s (Maung 2012) and although the total area converted remains low, future expansion is expected owing to increased international opportunities afforded by access to international markets (Webb *et al* 2014). That said, we acknowledge that given the aggregate nature of the land cover classification, we cannot unequivocally state that all the water body pixels represent aquaculture as a portion of those pixels could potentially be flooded rice paddies.

Other underlying drivers of mangrove loss transitions include weak law enforcement, resulting from the lack of sufficient funding and training across the country (Rao *et al* 2002). For example, illegal encroachment converted 40% of mangroves in

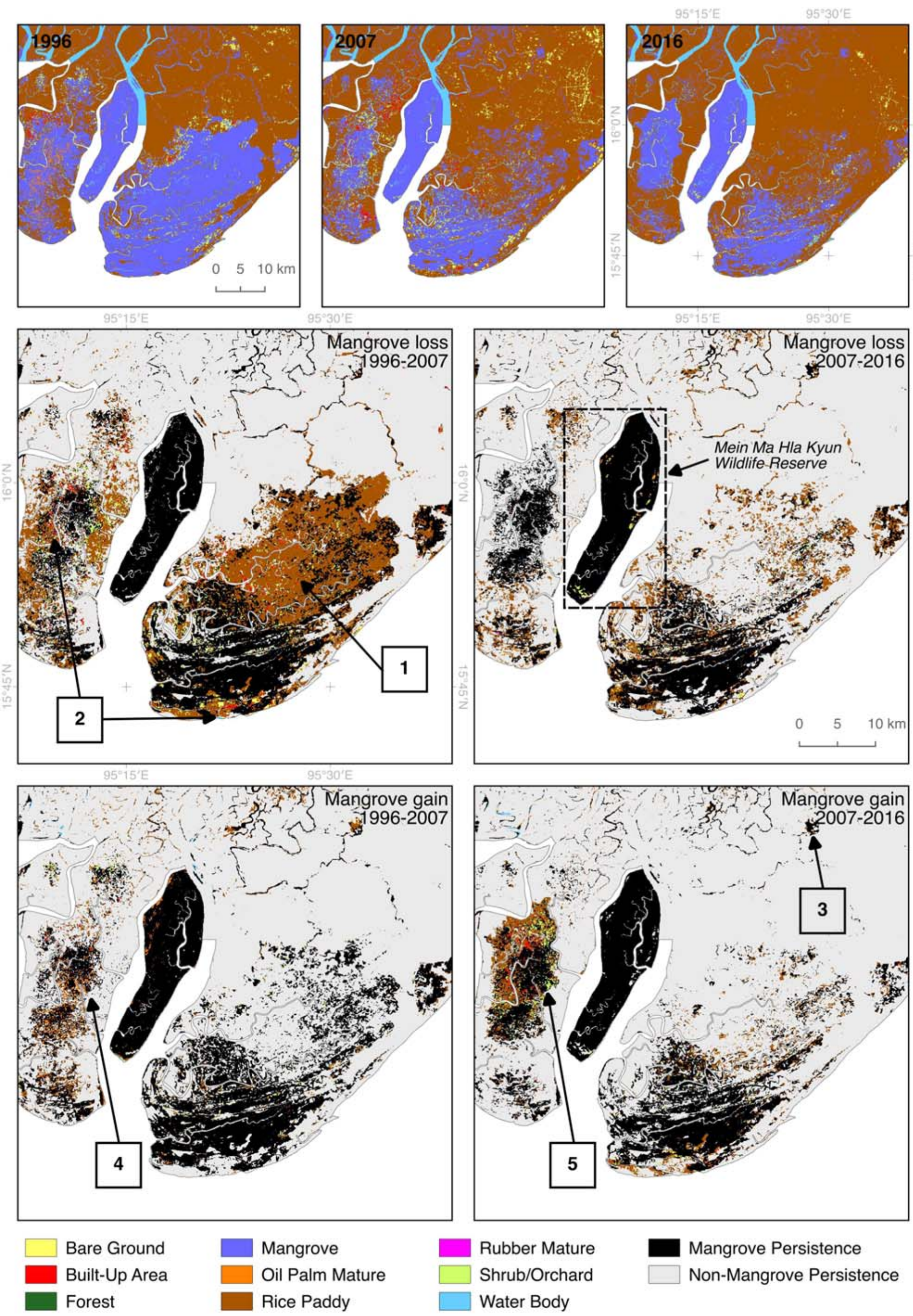

Figure 4. Land cover in 1996, 2007, 2016 (top panel) and mangrove loss and gain in 1996–2007 and 2007–2016 in Ayeyarwady Region. The Mein Ma Hla Kyun Wildlife Reserve held some of the remaining mangrove areas (i.e. mangrove persistence in both time-intervals covering the 20-year period) in the Ayeyarwady Delta. Mangrove conversion into rice paddies were much more extensive in I1 compared to I2, of which [1] shows extensive mangrove loss for rice paddy farming that were converted permanently. Some mangrove areas were converted into built-up areas [2], albeit this transition from mangrove to built-up is non-systematic. Mangrove gains in the Delta can be observed, of which [3] shows persistent areas of mangroves observed during I2 that came from mangrove gains from rice paddy during I1. Mangrove gains from oil palm were observed as a systematic transition during I1 [4]. Mangrove gains from rice paddy, shrub/orchard, and built-up area were also observed as non-systematic transitions [5].

Wunbaik Reserved Mangrove Forest in Rakhine State into shrimp farms and rice paddies (figure 5), along with degradation due to illegal wood cutting, brick-baking, and bark peeling (Stanley *et al* 2011, Stanley and Broadhead 2011, Saw and Kanzaki 2015), highlighting the challenges to contemporary protected area management in Myanmar. The Forest Department operated from 1972–2002 without a mangrove forest management working plan, but nevertheless implemented a quota system to meet revenue targets for fuelwood extraction and charcoal production, which greatly facilitated mangrove degradation (Oo 2002). Other broad underlying drivers of mangrove loss identified for Myanmar include increasing population density (Richards and Friess 2015), the low economic valuation attributed to mangrove resources compared

Table 2. Summary of systematic transitions of mangrove loss and mangrove gain in sub-national units of Myanmar at two time-intervals across a 20-year period. The land cover types included bare ground (BRG), built-up area (BUA), forest (FOR), mangrove (MNG), oil palm mature (OPM), rubber mature (RBR), rice paddy (RPD), shrub/orchard (SHB), water body (WTR).

	Mangrove loss				Mangrove gain			
	1st interval		2nd interval		1st interval		2nd interval	
Region/State	Target	Avoid	Target	Avoid	Target	Avoid	Target	Avoid
Ayeyarwady	OPM		OPM	BRG BUA FOR SHB	OPM	FOR RBR		FOR
Bago	BUA OPM RBR WTR	FOR	BUA OPM WTR	BRG FOR RBR SHB	OPM WTR	BRG FOR RBR SHB	OPM RBR WTR	FOR
Mon	BUA OPM RBR SHB	BRG WTR	OPM WTR	FOR	BRG BUA OPM WTR	FOR RBR SHB	BRG	FOR RBR SHB
Rakhine	BRG BUA RPD	FOR	OPM RPD WTR	FOR	BRG WTR	FOR RBR	RPD WTR	FOR RBR
Tanintharyi	BUA OPM RPD	FOR	OPM RPD WTR	FOR	BRG BUA RPD WTR	FOR RBR	BUA	FOR RBR
Yangon	OPM RBR WTR	BRG	OPM WTR	BRG BUA FOR RBR SHB	WTR	FOR RBR SHB	BRG OPM WTR	RBR SHB

to other non-mangrove resources (Oo 2002), and Myanmar's heavy dependency on biofuel-based energy needs as some mangrove species are widely used for firewood/charcoal due to high caloric content and prolonged burning capability (Veettil *et al* 2018).

Reversion of water bodies into mangrove was indicated as the most common targeted systematic gain by mangroves. This is not surprising given that retired aquaculture ponds may have little alternative use other than mangrove restoration (Stevenson *et al* 1999). Community-based mangrove reforestation programmes have been promoted by both government and non-government agencies, and have targeted abandoned agricultural land or degraded mangrove habitats (Zöckler *et al* 2013, Veettil *et al* 2018); these programmes have been buttressed by multiple pieces of legislation that protected Myanmar's mangroves and reinforced the role of local communities in forest management through participatory forest management bodies (e.g. 1992 Forest Law 1995 Forest Act, Locally Owned Forest Plot Directives, 1995 Policy of Myanmar Forest) (Oo 2002). Aside from active restoration or rehabilitation, mangrove forests can rapidly (re-)colonise open mudflats or abandoned aquaculture mudflats, provided that the geomorphological conditions are appropriate for mangrove establishment (Friess *et al* 2012). Finally, systematic transitions with bare ground along with field observations of mangrove gains along the coastlines (Bago, Mon, and Yangon) suggest newly accreted lands or 'wasteland' were targeted for mangrove reforestation initiatives.

4.2. Analysing gross land cover transitions provided robust insights on mangrove cover change

Whereas land cover and change estimates are expected to vary to a certain degree across studies, mangrove estimates have exhibited huge variance across studies (Friess and Webb 2014). Estoque *et al* (2018) revealed that using global datasets to infer national-level statistics—a practice facilitated by the introduction of global high-resolution forest change maps—may introduce severe inaccuracies, demonstrating the need for methods that are scale-relevant. In their study of mangrove cover change for Myanmar using Landsat data, they estimated 6668 km^2 of mangrove cover in 2000 with an annual net loss rate of 2.41% (recalculated using equation (7) in Puyravaud 2003 for the 2000–2014 period). An estimated 11 459 km^2 in 2000 based on our data (also calculated using equation (7) in Puyravaud 2003 for I1) and annual net loss rates of 3.60%–3.87% were higher than those estimates. They further estimated gross mangrove losses of 2047 km^2

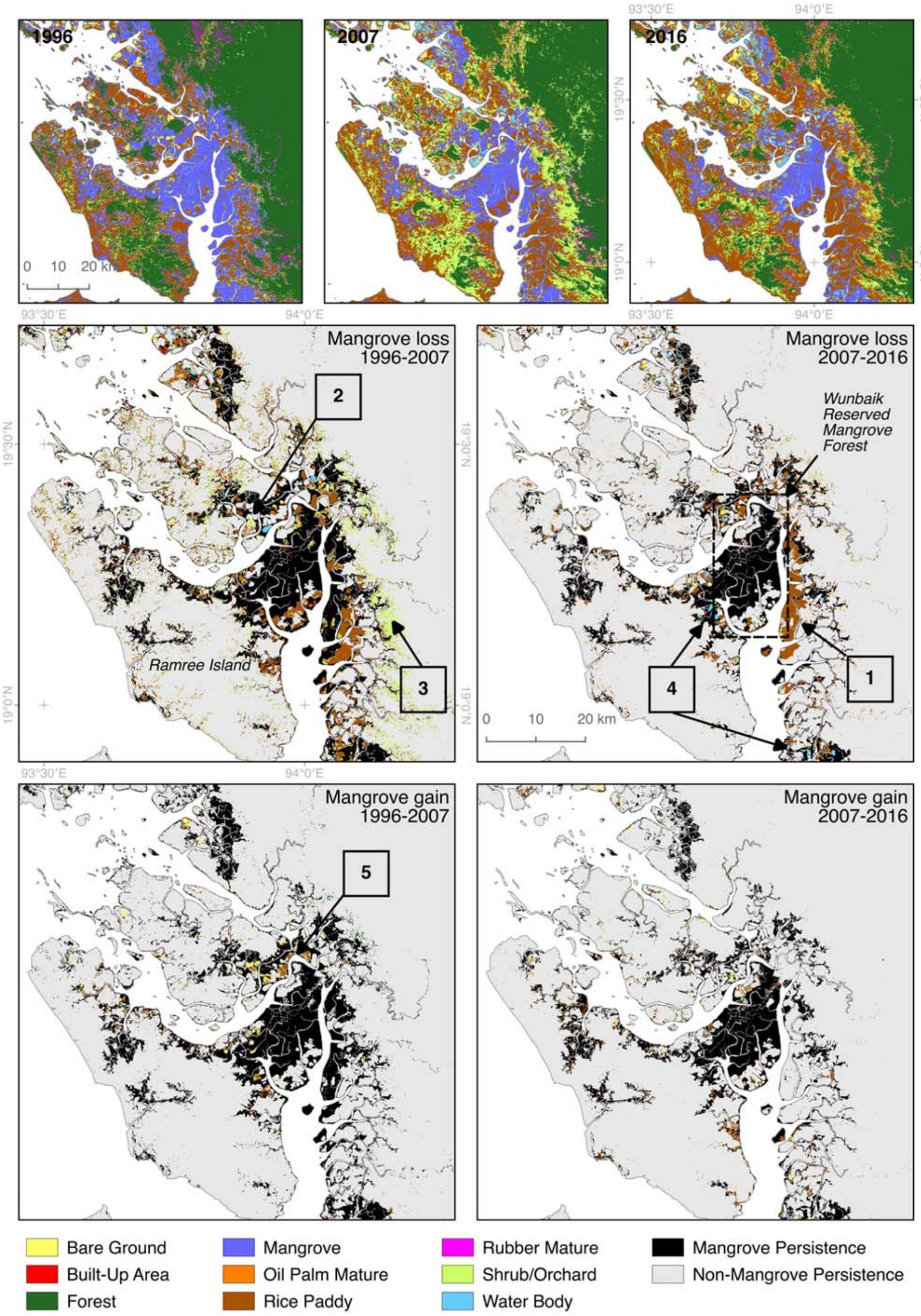

Figure 5. Land cover in 1996, 2007, 2016 (top panel) and mangrove loss and gain in 1996–2007 and 2007–2016 in Rakhine State. Large persistent mangrove areas remained in both time-intervals covering the 20-year period such as in Wunbaik Reserved Mangrove Forest towards the northeast portion of Ramree Island. Mangrove conversion into rice paddies was a systematic transition in both intervals, of which [1] shows rice paddy expansion during I2 through conversion of previously persistent mangrove areas during I1. Mangrove conversion during I1 into bare ground [2] was a systematic transition, whereas conversion into shrub/orchard [3] was a non-systematic transition. Mangrove loss into water body was observed as a systematic transition during I2 [4], which may indicate conversion of mangroves into aquaculture ponds. Mangroves that were gained from rice paddies during I1 were subsequently converted back into rice paddies during I2 [5].

(31% of 2000 mangrove extent) between 2000 and 2014, whereas we calculated more extensive losses of 6330 km^2 in I1 and 3588 km^2 in I2. However, their estimates, as well as most previous estimates, were based on Landsat data only, and with the utilisation of multi-sensor data, our estimates—which exhibited high accuracies for both land cover and mangrove change maps—revealed a greater mangrove extent in 1996, and a faster net deforestation rate than previous studies (figure 6; table 1). Our methods not only advance geospatial analysis of mangrove cover change and other land cover change assessments by incorporating multi-sensor satellite data, but in addition, reveal the complete dynamics of mangrove cover change by quantifying gross land cover transitions. We recognise, however, that area estimates reported in our study do

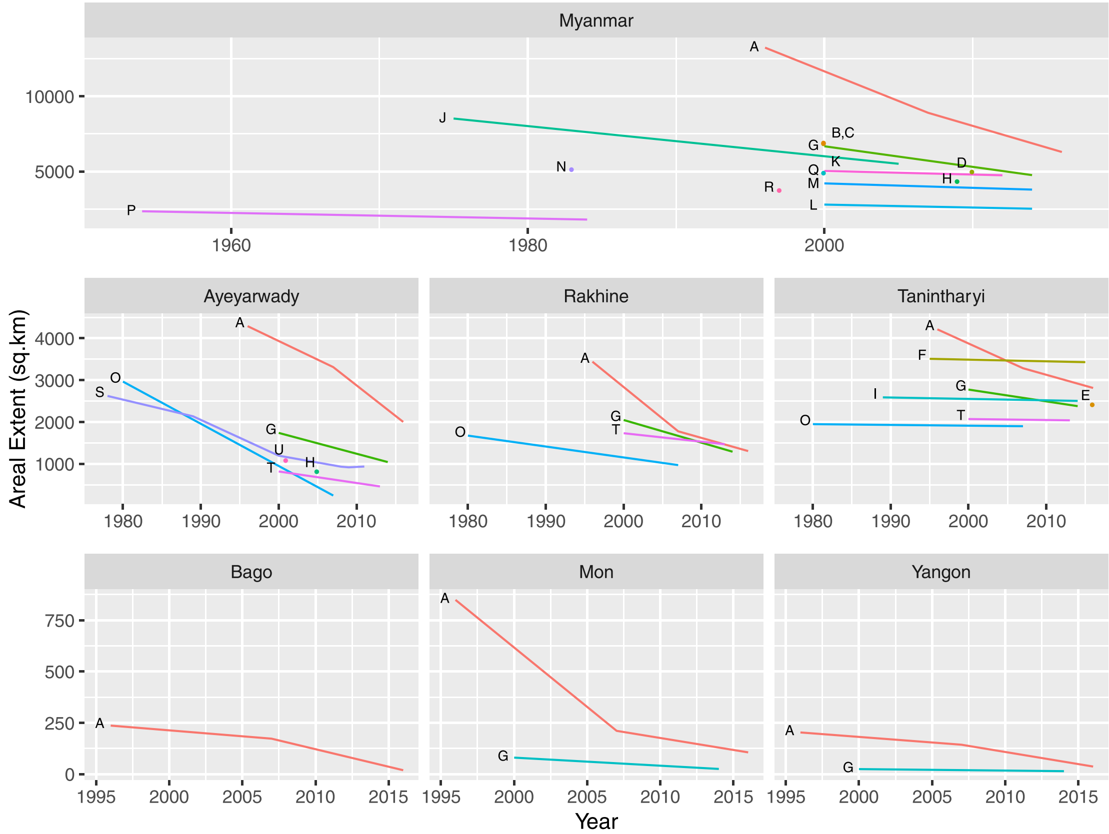

Figure 6. Comparison of reported mangrove areal extents for a specific year at country- and region/state-levels in Myanmar by various studies, including (A) this study, (B) Blasco and Aizpuru (2002), (C) Blasco *et al* (2001), (D) Bunting *et al* (2018), (E) Connette *et al* (2016), (F) De Alban *et al* (2018), (G) Estoque *et al* (2018), (H) FAO (2010), (I) Gaw *et al* (2018), (J) Giri *et al* (2008), (K) Giri *et al* (2011), (L) Hamilton and Casey (2016) using Mangrove Forests of the World data, (M) Hamilton and Casey (2016) using Terrestrial Ecoregions of the World data, (N) IUCN (1983), (O) Maung (2012), (P) Oo (2002), (Q) Richards and Friess (2015), (R) Spalding (1997), (S) Webb *et al* (2014), (T) Weber *et al* (2014), and (U) Zöckler *et al* (2013).

not reflect area adjustments accounted for by accuracy assessments given our above-mentioned considerations. The results of the two approaches we implemented for accuracy assessments (i.e. Aldwaik and Pontius 2013 and Olofsson *et al* 2014), nevertheless, lent greater confidence to our estimates and analysis of the proximate causes and underlying drivers of mangrove change.

Gross land cover change estimates are critical for a comprehensive evaluation of landscape change (Hansen *et al* 2010), thus representing the complete change dynamics for a region of interest. Through these calculations, we have demonstrated that Myanmar's mangrove deforestation crisis is in full swing and is the result of complex proximate and underlying drivers. Nearly two-thirds of (presumably) high-quality mangrove forest have been lost since 1996, either converted to another land cover type permanently, or temporarily and then replaced by lower quality early successional mangrove forest or plantation. This is important given the high ecosystem services value for mangroves, including protection from both tsunamis and storm surges (Dahdouh-Guebas *et al* 2005, Kathiresan and Rajendran 2005, Fritz *et al* 2009, Estoque *et al* 2018). It is important to recognise that although it is beneficial in the long run to rehabilitate degraded and deforested mangroves, a significant lag time will occur between the initiation of restoration and the maturation of those ecosystem services. Only by quantifying gross changes can variations in ecosystem services over time be accurately evaluated.

Aside from providing a fuller picture of mangrove deforestation dynamics, gross land cover change analysis facilitated the identification of land cover transitions, which as a result, revealed the complete dynamics of mangrove cover change, including the 'destination' classes for mangrove loss as well as the 'source' classes for mangrove gain. This allowed us to quantify the counterbalancing effect of mangrove restoration efforts, which led to mangrove gains in Ayeyarwady and Rakhine (Maung 2012, Aung *et al* 2013, Zöckler *et al* 2013, Veettil *et al* 2018) (table 1). In this case, while reforestation and natural regeneration were documented as contributing to positive gains in mangrove cover, it highlights the critical need to further invest in management strategies that aim to further increase gross mangrove gains. Gross land cover change analysis also allowed for a spatially explicit assessment of mangrove persistence, which could be critical in identifying core areas for protection, especially 'frontier' mangrove forests with relatively high conservation value (figures 3–5). Interventions could therefore include protection of remaining core areas of mangroves, potentially leading to improved conservation outcomes.

Moreover, gross change statistics are necessary for Intensity Analysis, which enabled us to determine with high confidence the proximate causes of mangrove change, including the relationship (i.e. systematic or not) between land cover types. While Intensity Analysis may not be necessary to reveal the most important proximate causes in terms of area, the identification of systematic transitions revealed a 'co-dependent' relationship between mangrove conversion and the gain of the destination land cover type. For example, the gains of oil palm, water bodies, and built-up areas in this study were dependent on mangrove loss in several sub-national units. While other studies used net statistics to impute oil palm and aquaculture as drivers of deforestation in Myanmar (Primavera 2006, Stibig *et al* 2014, Richards and Friess 2015), quantitative accounting of systematic transitions provides unassailable evidence of mangrove clearing for oil palm, or highlight intervention needs such as improved planning concerning aquaculture expansion in mangroves. This is particularly important as economic policies in Myanmar promote private sector investments in oil palm and aquaculture (Scurrah *et al* 2015, Belton *et al* 2018).

4.3. Recommendations

Gross land cover change analyses can be applied to assessments of emergent corporate 'zero deforestation' policies. High-profile corporate no-deforestation policies may, in fact, be 'zero net deforestation' policies (e.g. Colgate-Palmolive Company 2019, Unilever 2019), which could allow for gross losses as long as they are counterbalanced by gross gains through reforestation. Our study emphasises the fact that monitoring gross changes is an effective method to estimate the internal land cover change dynamics contributing to net deforestation with important implications for critically analysing the changes in ecosystem services associated with those policies.

The findings from our spatial analysis of mangrove change can help inform policymakers and planners in evaluating the impacts of the national government's agricultural modernisation policy as well as the effectiveness of mangrove restoration programmes or the management of protected areas where mangroves are found, and in designing site-specific strategies to keep remaining mangroves intact and to halt the further loss of mangroves. Our approach can also be applied in studying the change dynamics of mangroves elsewhere that can provide a deeper and more nuanced understanding of the associated drivers of mangrove change.

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Author contributions

- JDTDA and ELW conceived and designed the study.
- JDTDA, JBJ, and DWW conducted land cover data analysis, including development of scripts.
- JDTDA, JBJ, MMT, and ELW analysed and interpreted land cover change results.
- JBJ conducted literature review of causes and drivers of mangrove cover change.
- JDTDA, JBJ, and ELW wrote the manuscript.
- ELW secured funding for the study.
- All authors reviewed and commented on the manuscript.

Competing interests

The authors declare no conflict of interest.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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