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Assessing the conservation status of mangroves in Rakhine, Myanmar

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Abstract

1. Ecosystem degradation is a key challenge that human society faces, as ecosystems provide services that are tied to human well-being. Particularly, mangrove ecosystems provide important services to communities but are suffering heavy degradation, loss and potential collapse due to anthropogenic activities. The IUCN Red List of Ecosystems is a transparent and consistent framework for assessing ecosystems' risk of collapse and is increasingly used to inform legislation and ecosystem management globally.
2. Satellite data have become increasingly common in environmental monitoring due to their extensive spatial and temporal coverage. Here, recent advances in analyses using satellite-derived data were implemented to reassess the conservation status of the 'Rakhine mangrove forest on mud', an important intertidal ecosystem in Myanmar, extending a previous national Red List assessment that assessed the ecosystem as Critically Endangered.
3. By incorporating additional data sources and analyses, the extended assessment produced more robust results and reduced the uncertainty in the previous assessment. Overall, the ecosystem was assessed as Critically Endangered (range: Vulnerable to Critically Endangered) as a result of historical mangrove extent loss. Recent losses and biotic disruptions were also observed, which would have led to the ecosystem being assessed as Vulnerable.
4. While the final outcome of the Red List assessment remained at Critically Endangered due to the historical state of the mangroves pre-dating the temporal coverage from satellite data, the uncertainty of the ecosystem's status was reduced, and the reassessment highlighted the recent areal changes and mangrove degradation that has occurred.
5. The importance of conducting reassessments when new data become available is discussed, and a template for future mangrove Red List assessments that use satellite data as their primary source of information to improve the robustness of their results is presented.

KEYWORDS
ecosystem risk assessment; ecosystem risk of collapse; mangrove ecosystem; Rakhine, Myanmar; Red List of Ecosystems; satellite time series

1 | INTRODUCTION

Ecosystems around the world continue to be threatened by anthropogenic activity (Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services [IPBES], 2019). These threatening processes have led to reductions in biodiversity and decreased capacity for the delivery of ecosystem services, with important impacts on human well-being (Cardinale et al., 2012). To support effective conservation decision-making, there is a need for transparent and consistent methods for assessing the status of ecosystems based on sound ecological knowledge. The IUCN (International Union for the Conservation of Nature) Red List of Ecosystems was developed to assess and identify ecosystems at risk of losing biodiversity and ecological functions (Keith et al., 2013). The Red List was designed to be applicable to any terrestrial, marine or freshwater ecosystems and since its inception has been applied to >4000 ecosystems across >100 countries (Bland et al., 2019; http://iucnrle.org).

The Red List of Ecosystems is a standardized framework that enables estimates of relative risk of ecosystem collapse; collapse is the endpoint of ecosystem decline when defining biotic or abiotic features are lost and the characteristic native biota are no longer sustained (Keith et al., 2013). The Red List enables consistent national- and international-level ecosystem assessments that can be used to inform legislation and ecosystem management (Bland et al., 2019; Keith et al., 2013). The Red List of Ecosystems framework comprises five criteria (each with additional sub-criteria) that reflect symptoms of ecosystem change. Criterion A uses measures of change in ecosystem area over time, where ecosystems with greater areal losses are at a higher risk of collapse. Criterion B identifies ecosystems at risk of collapse from spatially explicit, stochastic threats using specific metrics and thresholds of ecosystem size, where smaller ecosystems are at a higher risk of collapse. Criterion C estimates the risk associated with environmental degradation related to key physical and abiotic processes, and Criterion D estimates the risk associated with degradation to key biota and/or ecological interactions or processes, where the loss of either of these leads to a transformation of the identity of the ecosystem. Finally, Criterion E allows the use of simulation models to directly estimate an ecosystem's probability of collapse within a fixed time frame (Keith et al., 2013). Full details of the criteria can be found in the Red List of Ecosystems guidelines (Bland et al., 2017; Keith et al., 2015; Rodríguez et al., 2015).

Myanmar is one of the most forested countries in Southeast Asia (Leimgruber et al., 2005), supporting a large number of endemic species with important economic and cultural significance to the country (Aung, 2007; Murray et al., 2020). Despite the importance of Myanmar's ecosystems, they are facing increasing anthropogenic threats as the country continues to develop and its population grows (Veettil et al., 2018; Webb et al., 2014). A national Red List assessment of all terrestrial ecosystems in Myanmar was completed in 2020 to support conservation efforts (Murray et al., 2020). These assessments provide information for all 64 terrestrial and coastal ecosystems in Myanmar, highlighting the ecosystems most at risk, along with data-deficient ecosystems that will require additional research attention to inform appropriate conservation actions.

Mangrove ecosystems occur globally along tropical and warm temperate coastlines and play critical economic and ecological roles for human communities and the surrounding ecosystems. They provide a wide range of ecosystem services, acting as sources of food and fuel for local communities; nursery sites for ecologically, subsistence and commercially important faunal species; and coastal protection from storm events and are carbon-rich ecosystems aiding in climate regulation (Goldberg et al., 2020; Lee et al., 2014; Richards & Friess, 2016; Veettil et al., 2018). Myanmar is one of the most mangrove-rich countries in the world (Estoque et al., 2018), and mangrove ecosystems are particularly important along the coast of the country, as the majority of the human communities here rely on mangroves in their daily activities (Storey, 2015). Despite their importance, Myanmar is a hotspot for mangrove loss (De Alban et al., 2020; Goldberg et al., 2020) and is one of six nations in Southeast Asia that together contribute to nearly 80% of total global anthropogenic mangrove loss over the past two decades (Goldberg et al., 2020).

Studies on the mangrove ecosystems in Myanmar are often at a national level (De Alban et al., 2020; Estoque et al., 2018) or focused on the Ayeyarwady delta (Webb et al., 2014; Win et al., 2020), and the mangroves on the west coast of Myanmar along the Bay of Bengal are relatively less studied. Neighbouring mangrove ecosystems in the Sundarbans and Bangladesh to the north and along the Ayeyarwady delta to the south have experienced well-documented mangrove losses in the past few decades (De Alban et al., 2020; Sievers et al., 2020). Here, the focus is on the 'Rakhine mangrove forest on mud', one of four mangrove ecosystems in Myanmar (Murray et al., 2020). The national Red List assessment for this ecosystem assessed it as Critically Endangered (Vulnerable–Critically Endangered) (Murray et al., 2020), making it one of the most at-risk ecosystems assessed in Myanmar. However, it also contained considerable uncertainty: For example, the estimated change in distribution over 50 years was based on only three Landsat images from 1988, 2000 and 2015 (Storey, 2015), while the historical mangrove change since 1750 was based on questionnaires that were from only five villages in the northern parts of the state (Storey, 2015). The assessment of mangrove ecosystem degradation was also based on a global study of mangroves that lack regional context.

Knowledge and data on mangrove status are rapidly improving due to improved satellite analysis methodology, larger satellite image archives, and a better understanding about mangrove threats and degradation dynamics. This assessment aims to use these advances to provide the first-recorded reassessment of any ecosystem in Asia under the Red List of Ecosystems criteria, revealing finer scale patterns of degradation and areal change while demonstrating how ecosystem status assessments can integrate newly acquired knowledge.

The Red List guidelines were used to integrate diverse sources of independent data and evidence, including various temporal scales of mangrove distribution maps from freely available sources; results from previous assessments of the ecosystem and newly developed methods, including a dense time-series satellite remote sensing data to estimate ecosystem area trends (Lee et al., 2021); and a mangrove conceptual model to train a mangrove degradation model specific for this ecosystem (Lee et al., 2021) into a single outcome assessing the risk of ecosystem collapse. Within the context of Red List assessments, reassessments are vital as ecosystems continue to change and/or additional data or novel analytical methods become available, potentially changing the outcome of the assessment. In this study, the same ecosystem description as the previous assessment was used to ensure identical units of assessment and that any differences in the outcome are due to the added information or new methods. By conducting a reassessment, we aimed to reduce the uncertainty associated with the initial assessment and further improve our understanding of the status of the ecosystem, the threats it faces, the primary biotic and abiotic factors driving the risk of ecosystem collapse and the conservation actions that will be required to mitigate and reduce this risk.

2 | MATERIAL AND METHODS

The Red List of Ecosystems criteria according to the IUCN guidelines (Bland et al., 2017) was applied to assess the risk of collapse of the principal 'Rakhine mangrove forest on mud' ecosystem along Myanmar's north-west coast (Figure 1), hereafter referred to as 'Rakhine mangroves'. Existing data for the region that were potentially suitable for assessing each of the five criteria were reviewed, including data collated by Murray et al. (2020). These data were supplemented with additional analyses of satellite data using recently developed methods for mapping time-series ecosystem change and degradation; the breakdown of the workflow is shown in Figure 2. A detailed description of the assessment, including methods and findings, can be found in the Supporting Information.

2.1 | Ecosystem description

Rakhine mangrove ecosystem is defined by the extent of mangrove-dominated vegetation along Myanmar's coastline within the Bay of Bengal, including all mangroves on a muddy substrate within Rakhine state and Bassein, Ayeyarwady (Murray et al., 2020). The ecosystem is classified under the IUCN Global Ecosystem Typology as functional group MFT1.2 intertidal forests and shrublands of the brackish intertidal biome (Keith et al., 2020; MFT1.2, https://global-ecosystems.org/explore/groups/MFT1.2), and under the IUCN Habitats Classification Scheme (Version 3.1) as habitat type 12.7 (Mangrove Submerged Roots) (IUCN, 2012). It occurs within the Bay of Bengal marine ecoregion (Eco ID 321) (Spalding et al., 2007).

Rakhine mangroves differ from neighbouring mangrove ecosystems by occurring across four geomorphic settings (deltaic, open coast, lagoonal and estuarine), in contrast to the solely deltaic mangroves of the Sundarbans and Ayeyarwady (Worthington et al., 2020). The ecosystem consists of at least 28 true mangrove species (Table S1), including the Critically Endangered *Bruguiera hainesii* and *Sonneratia griffithii* (IUCN, 2020; Myint & Stanley, 2011). The faunal diversity of the ecosystem is also high, including at least 62 species of fin fish; five species of crustacean; five species of mollusc; 104 bird species, including both migrants and residents; and several globally endangered vertebrates (Table S2; Stanley & Broadhead, 2011).

Myanmar receives approximately 75% of its annual rainfall during the summer monsoon months (June–September); Rakhine is the state that receives the highest seasonal rainfall (>424 cm) during this period (Sen Roy & Kaur, 2000). This high rainfall, combined with the flow of low-salinity water from the Ganges–Brahmaputra River in the north, leads to a low salinity of <18 parts per thousand (ppt) during the summer monsoon season. Salinity increases to more than 34 ppt in the dry seasons due to low rainfall and regular inundation of highly saline waters flowing from the Andaman Sea in the south (Ramaswamy & Rao, 2014). The coastline receives a small amount of sediment discharge from the Ganges–Brahmaputra delta to the north and the Ayeyarwady delta to the south. These salinity and sedimentation regimes are key components of the abiotic environment for this ecosystem, as mangroves occur along the mesotidal coastal zone in areas where soft sediment is regularly inundated throughout the tidal cycle (Ramaswamy & Rao, 2014; Worthington et al., 2020).

2.1.1 | Threatening processes, drivers and ecosystem decline

Rakhine mangroves are subject to anthropogenic, natural and climate change-related threats (Figure 3). Mangrove loss and degradation in Rakhine are driven predominantly by anthropogenic activities, in particular their conversion to agricultural and aquacultural lands, including oil palm plantations, rice paddies and shrimp farms (De Alban et al., 2020; Goldberg et al., 2020; Storey, 2015). The development of agriculture and aquaculture near mangroves can also result indirectly in ecosystem degradation due to sea wall construction, altering normal hydrology and changing the tidal inundation dynamics, influencing the mangrove ecosystem. Farms can also directly introduce pollutants, causing eutrophication of mangrove

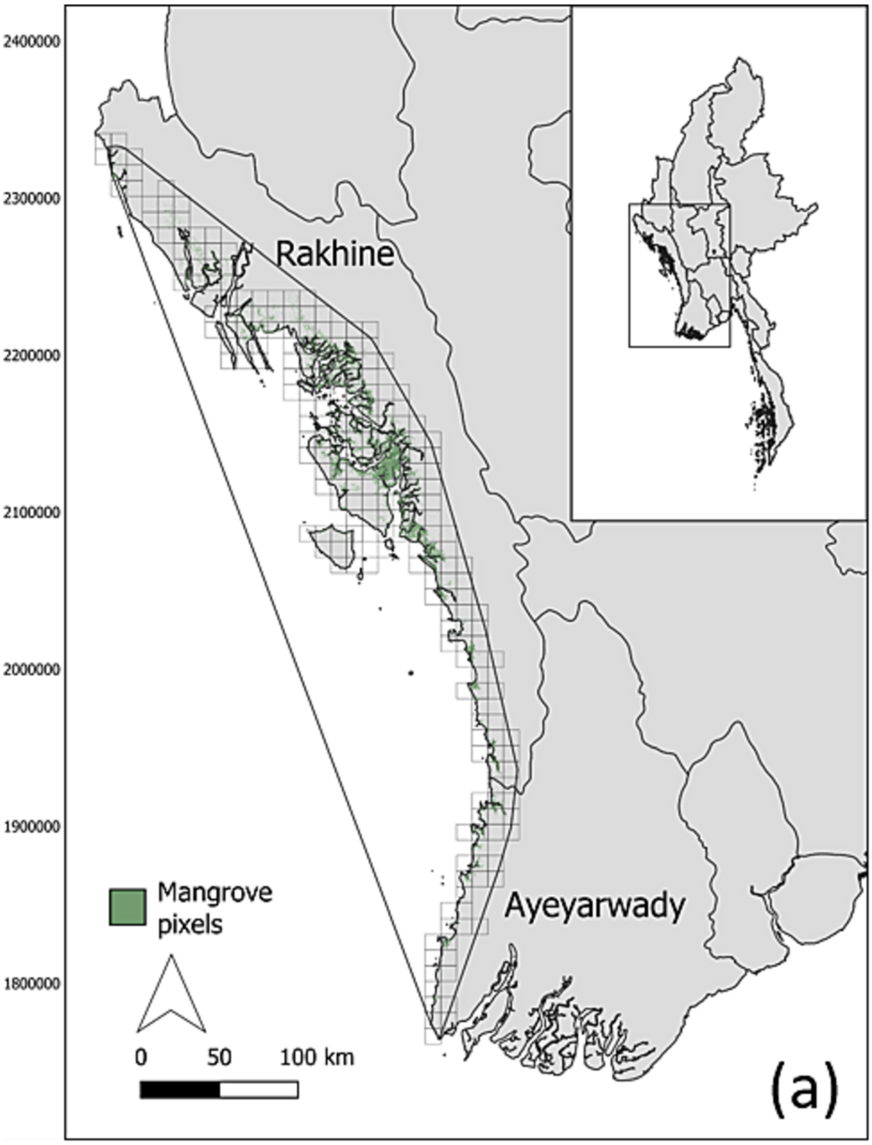

FIGURE 1 (a) Mapped distribution of the Rakhine mangrove forest on mud and the location of the study region within Myanmar (top right). The map also includes occupied 10-km^2 grid cells and a minimum convex polygon encompassing all mangrove occurrences within the study region. (b) Photo of the ecosystem within the Wunbaik reserved forest (photo credit: Don Macintosh).

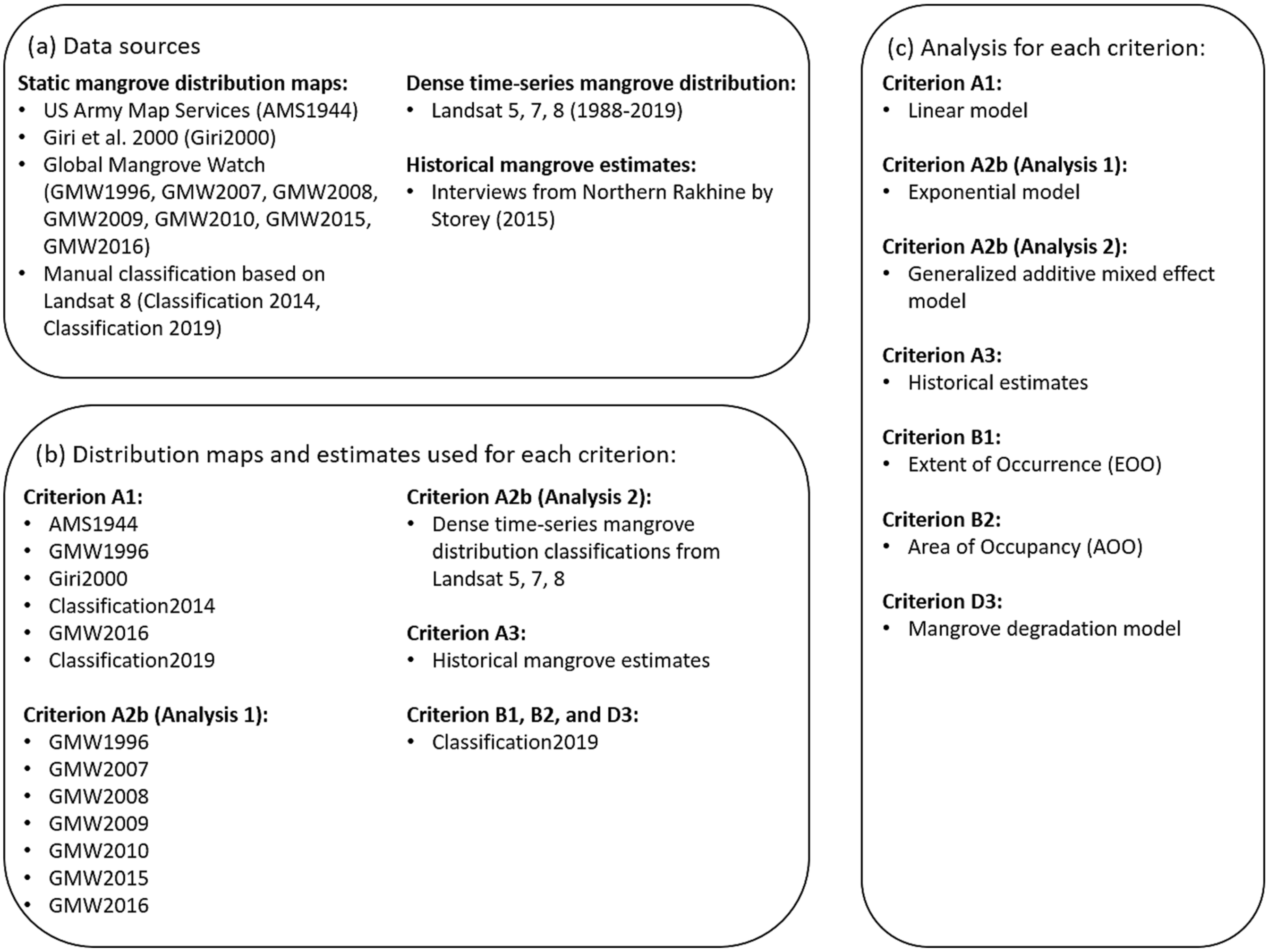

FIGURE 2 Overall workflow of the methods, including (a) the data sources used and (b) distribution maps and estimates and (c) analysis done for each criterion of the Red List of Ecosystems assessment.

ecosystems (Friess et al., 2019). Logging and wood harvesting for firewood and charcoal and bark peeling for dyes are other sources of degradation to the Rakhine mangroves (Stanley & Broadhead, 2011). Relative sea-level rise as a result of climate change is also expected to negatively affect Rakhine mangroves by reducing land suitable for mangroves, thus reducing their area (Alongi, 2015). Climate change-driven increased frequency and intensity of storms, altered precipitation and higher temperatures may also threaten the ecosystem in the future (Alongi, 2015; Ward et al., 2016).

2.1.2 | Indicators and thresholds of ecosystem degradation and collapse

Mangrove ecosystems are primarily characterized by mangrove trees and shrubs acting as foundation species, with non-dominant animal species playing smaller ecological roles (Geist et al., 2012; Marshall et al., 2018). Therefore, mangrove vegetation loss or degradation was used as an indicator of collapse risk, where an absence of true mangrove species signifies the collapse of the ecosystem (Marshall et al., 2018).

When assessing the spatial Red List criteria (Criteria A and B) of Rakhine mangroves, the ecosystem is considered to have collapsed when pixel-specific mapped mangrove distribution is reduced to zero as a result of the complete loss of any mangrove vegetation. For Criterion C, a sufficient change in abiotic conditions, such as sedimentation and/or salinity, can cause mangrove collapse when the environment can no longer sustain mangrove vegetation (Krauss et al., 2014; Peters et al., 2020). For Criterion D, the ecosystem is considered collapsed when mangrove vegetation is degraded to the point of complete loss of distribution (cf. function); see more details below under Criterion D.

2.2 | Mapping distribution and degradation of Rakhine mangroves

To assess Rakhine mangroves under the Red List criteria, various maps of mangrove distribution at different times across the assessment period are needed. To achieve this, multiple independent sources of data to generate mangrove area estimates, each with their

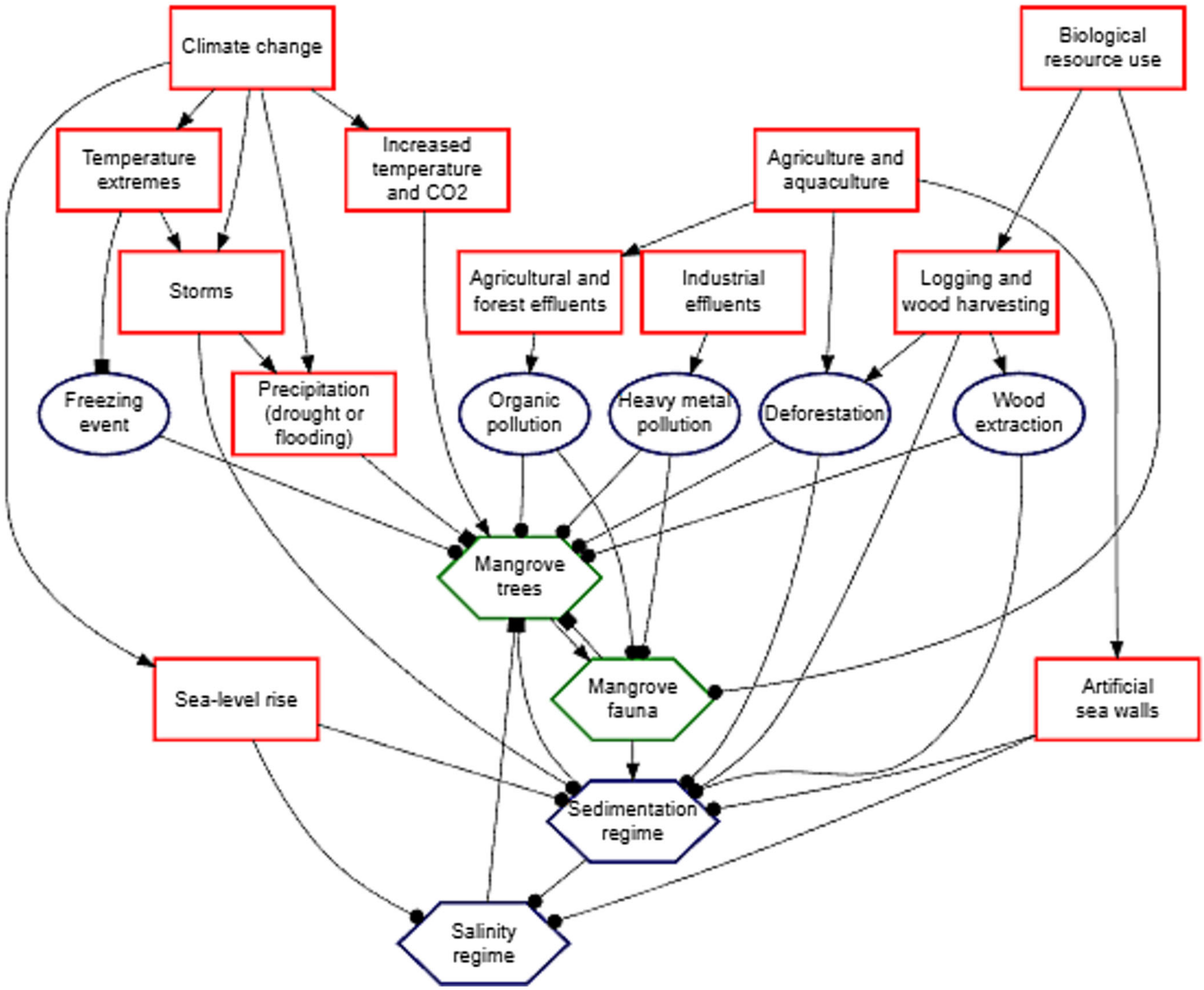

FIGURE 3 Mangrove ecosystem conceptual model highlighting the main threats and ecological processes. The red boxes indicate threats, the blue ovals represent the abiotic processes, the blue hexagons represent the abiotic environment and the green hexagons represent the biotic components of the mangrove ecosystem. Pointed arrowheads indicate positive effects, rounded arrowheads indicate negative effects and square arrowheads indicate context-dependent effects.

respective accuracy assessments, were compiled and reviewed. Including multiple sources of data and analytical methods can increase confidence in the robustness of the Red List assessment outcomes (Bland et al., 2017).

2.2.1 | Static mangrove distribution maps

Maps of Rakhine mangrove distribution were needed to assess distribution change over time, as well as assess the extent of ecosystem degradation. Four sources of static maps suitable for the assessment over different time periods were used to investigate changes in the distribution of Rakhine mangroves over time. Additional steps were taken to ensure the comparability of the data from different sources when they were used together in a single analysis:

1. the US Army Map Services (AMS) for Burma (Myanmar) created from aerial photography and depicting mangrove distribution for the period between 1943 and 1945 (**AMS1944**), which were digitized manually (details in Supporting Information);
2. a freely available global mangrove map for 2000 produced by Giri et al. (2011) from Landsat satellite data (**Giri2000**);
3. Global Mangrove Watch (GMW) version 2 maps with their associated accuracy assessments, available for various years: **GMW1996**, **GMW2007**, **GMW2008**, **GMW2009**, **GMW2010**, **GMW2015** and **GMW2016** (Bunting et al., 2018). GMW was included as it is one of the most recognized global datasets for mangrove monitoring, providing time series information for global mangrove areas, and is freely available to the public. GMW provides straightforward mangrove area estimates to users without further capacity to develop their own classifications. The

overall accuracy of the dataset was 95.3%, with a 99% likelihood that the confidence interval, using the Wilson score interval, was 4.5%–5.0%.

4. Two additional mangrove distribution maps for the years 2014 and 2019 were classified using a machine learning model for the study region; 2014 was chosen as the earliest year with complete Landsat 8 coverage, and 2019 was chosen as the latest year with complete Landsat 8 coverage at the time of analysis. The 2019 map was used for the assessments of Criteria B, C and D. Manually developing these two maps allowed accuracy assessments to be conducted for these maps, reporting area estimates with quantitative uncertainties. These maps were produced by applying supervised random forest classifications to cloud-free composites of Landsat 8 images acquired during the dry season (January to March, October to December) for those 2 years using the Google Earth Engine (Gorelick et al., 2017; details provided in the Supporting Information) and are referred to as **Classification2014** and **Classification2019**.

Classification2019 was used for any analysis where only one map of mangrove distribution was required, while all other maps were used in conjunction with others for trend analyses to estimate mangrove area change through time (Figure 2b).

2.2.2 | Dense time series of mangrove distribution

In addition to estimating mangrove areas from static mangrove maps that provide estimations of mangrove areas at specific times, a dense Landsat time-series model was developed to estimate mangrove area trends from 1988 to 2019 following the methods of Lee et al. (2021). This included using random forest models to estimate mangrove areas from every available Landsat image over the study area. To train the random forest models, a spectral library suitable for training and prediction was developed. The training points used to generate the spectral library included target classes (mangrove; water; cloud; others, which include all non-mangrove non-water land cover such as non-mangrove forests, sand and bare ground) for each of Landsats 5, 7 and 8 using high-resolution Google Earth imagery (National Centre for Space Studies [CNES]/Airbus) for 2012 (Landsat 5) and 2018 (Landsats 7 and 8). Landsat bands were then extracted from each of the training points from their respective Landsat satellites to generate a set of explanatory covariates included in the spectral library. To develop an image time series suitable for applying the dense time-series classification model, 16-day repeat mosaics were created for the entire study region for the period 1988 to 2019. Random forest models trained using the spectral libraries were used to predict the land cover of each of these mosaics, creating maps of mangroves, water, others and clouds. Estimates from mosaics where there were any gaps in mapped distribution were discarded, leaving 1132 estimates to enable analyses of mangrove areal trends over a 31-year period. The accuracy of the dense time-series classification model was assessed with 900 validation points, including 200 validation points that were consistently mapped as mangroves in AMS1944, Giri2000, GMW1996, GMW2016 and Classification2019 and 700 validation points that were never mapped as mangroves in the same maps. All 900 validation points were then applied to the 1132 classified maps, and all points classified as clouds were discarded, leaving 174,487 mangrove pixels and 590,895 non-mangrove pixels that were used to assess the entire dense time series. The results from these pixels were subsequently used to estimate the accuracy of the dense time-series classification model.

2.2.3 | Mapping mangrove degradation

To assess the extent of ecosystem degradation in the Rakhine mangrove ecosystem, an additional supervised random forest classification model, trained to classify mangrove pixels into degraded and intact classes, was used (Lee et al., 2021). Occurrence points used to train the classification model were collected following the criteria below (for details, please refer to Lee et al., 2021).

For a pixel to be labelled as intact in the training set, it must meet the following criteria:

- It contained part of a mangrove forest patch that was at least 5 ha in area.
- It contained a closed canopy cover with no underlying substrate observed from Google Earth imagery.
- It contained no obvious anthropogenic structures and disturbances observed from Google Earth imagery.
- It maintained the above criteria for at least 5 years.

Pixels in the training set annotated as degraded met the following criteria:

- Mangrove trees can be observed in Google Earth imagery (thus not collapsed).
- Low canopy cover and/or isolated trees can be observed from Google Earth imagery.
- Browning and/or tree death is observable from Google Earth imagery.

Training points representing the two classes of ecosystem state (157 degraded and 133 intact) were selected manually using Google Earth imagery across the study region. The training points were subsequently used to train a random forest classifier that included five explanatory variables: annual normalized difference vegetation index (NDVI) standard deviation and mean, annual normalized difference moisture index (NDMI) standard deviation and mean and annual normalized difference water index (NDWI) mean (Lee et al., 2021; Table 1). The analysis yielded two maps of degradation for Rakhine mangroves (2014 and 2019). The accuracy of these maps and the area of each class were subsequently estimated following good practice guidelines (Olofsson et al., 2014).

TABLE 1 Satellite-derived covariates used to model mangrove degradation including the expected mechanism for each covariate to detect mangrove degradation.

Covariate	Proposed mechanism	Reference
Annual NDVI mean	Intact mangrove forests have higher mean NDVI as they are more photosynthetically active and have higher canopy cover and LAI.	Kovacs et al. (2004)
Annual NDVI SD	Intact mangroves have a more stable NDVI as they remain productive and have high cover throughout the year as evergreen trees.	Verbesselt et al. (2016)
Annual NDMI mean	Intact mangroves with higher canopy cover have higher average NDMI.	Lucas et al. (2020)
Annual NDMI SD	Intact mangroves have a more stable NDMI as they remain productive and have high cover throughout the year as evergreen trees.	Verbesselt et al. (2016)
Annual NDWI mean	Intact mangrove forests have lower average NDWI as they have higher canopy cover and multi-spectral satellites cannot typically detect underlying water.	

Abbreviations: LAI, leaf area index; NDMI, normalized difference moisture index; NDVI, normalized difference vegetation index; SD, standard deviation.

2.3 | Red List of Ecosystems assessment

2.3.1 | Criterion A—reduction in geographic distribution

To obtain a comprehensive picture of the change in geographic distribution of the Rakhine mangrove ecosystem and consider any uncertainty that may exist, three independent analyses were developed to investigate its change through time. Additionally, the results from a previous study that estimated historical losses of Rakhine mangroves are also reported (Storey, 2015).

To estimate reduction in mangrove extent over *the past 50 years* (*Criterion A1*), linear and exponential models (after Bland et al., 2017) were fitted to six static area estimates (AMS1944, GMW1996, Giri2000, Classification2014, GMW2016, and Classification2019). Only two out of the seven available GMW maps (1996 and 2016) were included to prevent the model from being driven primarily by them. To allow comparison between the different data sources, each map was resampled to 200-m spatial resolution, which was larger than the smallest patch of mangroves depicted in the maps from the AMS (approximately 200 m × 200 m), while all other maps were originally at 30-m resolution. While accuracy metrics were not available for AMS1944, this map was generated from aerial photography by the US Army and included high levels of detail. Uncertainty may have arisen due to misclassification of mangroves by the cartographers, but there is unfortunately no method of assessing this. Regardless, given their level of detail and inclusion of mangroves as a specific class, this dataset provides a valuable historical baseline to compare against (Murray et al., 2014). The uncertainties within the maps are accounted for using statistical models, and the use of multiple independent sources of area estimates increases the robustness of the trend estimates (Bland et al., 2017). A pixel counting approach was used to estimate mangrove area from each map, as reference data were not available for the older maps to allow for area estimation using error matrices (Olofsson et al., 2014). The estimates and 95% confidence intervals from the models were used as best-case and worst-case scenarios to assess Criterion A1.

To estimate reduction in mangrove extent over *any 50-year period* (*Criterion A2b*), two analyses were performed. First, seven area estimates were derived from GMW, estimated at 30-m resolution using pixel counting. This dataset included data over a 20-year time frame, and in the absence of available socio-economic data to provide information about the most likely trajectory over 50 years, a statistical method was used to determine the most suitable model. Linear and exponential models were fitted to the dataset (Bland et al., 2017). These models were used to extrapolate the results into the future to include the 50-year time frame (1996–2046; beginning from the first GMW estimate), and the best and worst case scenarios were estimated based on the estimates and their 95% confidence intervals, the results representing the outcome of the assessment under Criterion A2b. Second, the dense time-series model described in Section 2.2.2 was used. A generalized additive mixed model (GAMM) was fitted to the area estimate from the dense time-series model, and the trend in extent was estimated using the R package mgcv (Wood, 2017). The estimate and 95% confidence intervals were then extrapolated to the required 50-year time frame (1988–2038; beginning from the first available Landsat image used), using both the absolute rate of decline and proportional rate of decline and the best and worst case scenarios calculated to assess the ecosystem under Criterion A2b.

To estimate reduction in mangrove extent *when compared to a historical baseline* (approximately 1750; *Criterion A3*), two different methods were used. First, previously published historical estimates of mangrove areas, obtained from interviews conducted in five villages in Northern Rakhine (Storey, 2015), were used. The estimate from this method assumes that the rate of mangrove loss was the same throughout the geographic extent of the ecosystem. Second, the mangrove area estimates from the various maps collated (AMS1944, GMW1996, Giri2000, Classification2014, GMW2016, and Classification2019) were extrapolated backwards to 1750. Assuming a constant rate of mangrove loss, both proportional loss and absolute area loss were estimated to generate best and worst case scenarios. The assumption that mangrove loss occurred at a constant rate was unlikely to hold true, as development within Rakhine did not occur at the same rate throughout the region (Storey, 2015), and a constant rate of loss over such a long time period is very unlikely. Regardless, these results provide the only source of plausible estimates possible, given data limitations, on historical mangrove change required for the Red List assessment.

2.3.2 | Criterion B—restricted geographic distribution

To assess Rakhine mangroves under Criteria B1 and B2, the Rakhine mangrove map produced for 2019 (Classification2019, Section 2.2.1) was used. The extent of occurrence (EOO, *Criterion B1*) was calculated using a minimum convex polygon enclosing all mapped occurrences of the ecosystem. The area of occupancy (AOO, *Criterion B2*) was calculated by counting the number of 10 km × 10 km grid cells that contained the ecosystem while accounting for geometric uncertainty (i.e., the placement of the cells used to assess AOO; Lee et al., 2019). Both of these functions were calculated using the R package *redlistr* (Lee et al., 2019). In addition to the EOO and AOO of the ecosystem, one of three sub-criteria had to be met for an ecosystem to be listed under Criteria B1 and B2: (a) an observed or inferred continuing decline, (b) an observed or inferred threat and (c) the ecosystem existing at a small number of threat-defined locations (Bland et al., 2017). As there is already evidence that there is a continuing decline in the extent of the Rakhine mangrove ecosystem based on results for Criterion A (i.e., Sub-criteria a and b are met), there was no need to estimate the number of threat-defined locations of the ecosystem (Sub-criterion c).

2.3.3 | Criterion C—environmental degradation

Environmental degradation of Rakhine mangroves can be caused by various drivers, including altered hydrology and pollution as a result of aquaculture, extreme weather phenomena and relative sea-level rise. Data on aquaculture expansion in the area and the effects these farms may have on surrounding mangroves would be required to assess Criterion C for Rakhine mangroves due to the expansion of aquaculture, none of which were available at the time of analysis. Data on future risks from extreme weather phenomena were also unavailable. As a result, only relative sea-level rise was assessed as the threat that can cause environmental degradation leading to ecosystem collapse.

While the Sea Level Affecting Marsh Model (SLAMM; Clough et al., 2016) is a commonly used model to predict future scales of relative sea-level rise along coastlines, the data required to parameterize and train such a model for the study region were not available. Thus, a sea-level rise model for the Indo-Pacific developed by Lovelock et al. (2015) was used, as reported by Murray et al. (2020). This was trained using the surface elevation table-marker horizon (SET-MH) method along with satellite-derived total suspended matter data to predict the year of submergence of mangroves in 10-year time steps. The relative severity of relative sea-level rise was estimated by assuming any mangroves predicted to be submerged in 50 years will be extensively degraded and likely to collapse due to drowning.

2.3.4 | Criterion D—disruption of biotic processes and interactions

The relative severity of the mapped degradation, including a range of plausible values, was estimated based on the training set that was used to develop the degradation model. As all training points for the degraded class were based on mangroves that were visibly degraded in high-resolution satellite imagery, substantial disruption to normal biotic processes must already have occurred, suggesting a high relative severity of degradation. The results from these models were used to estimate the extent of degradation for Rakhine mangroves for 2014 and 2019. The areas from each map and corresponding uncertainties were estimated following Olofsson et al. (2014).

However, the Red List requires assessments to consider change over 50 years, and a 5-year period is not sufficient to extrapolate the results to the required time frame. As a result, the ecosystem was assessed under *Criterion D3* by comparing the results for 2019 with a historical baseline (1750s). In this scenario, it is assumed that no ecosystem degradation was present in the 1750s due to low human population density and no evidence of mangrove degradation in the region before the 1800s (Storey, 2015). Additionally, the results from the assessment by Murray et al. (2020), who assessed ecosystem degradation using a model that evaluated trends in 12 vegetation indices for mangrove pixels mapped by GMW (Worthington & Spalding, 2018), were also reported to maintain comparability between the two assessments.

2.3.5 | Criterion E—quantitative risk analysis

Quantitative models that explicitly estimate the future risk of ecosystem collapse are required to assess an ecosystem under Criterion E (Bland et al., 2017). Such models should produce quantitative estimates of ecosystem risk of collapse over a 50- to 100-year time frame with explicit uncertainty. Existing quantitative mangrove models that may be suitable for assessing Rakhine mangroves' risk of collapse were reviewed. Process-based vegetation models may be suitable for assessing mangrove ecosystems under Criterion E but are data and computationally expensive when applied at the scale required for this study. The most suitable potential model, the MANGRO model (Doyle et al., 2003), was developed for mangroves in North America, where mangrove species diversity is much lower, and the assumptions and baseline data underpinning this model will not be appropriate to Rakhine mangroves. Thus, Criterion E was not assessed.

3 | RESULTS

3.1 | Criterion A

3.1.1 | Criterion A1

The analysis showed that Rakhine mangroves' historical distribution declined from the initial estimate of 2771 km^2 in 1943 to 1566 km^2 in

2019 (−43.8%, Figure 4). The best fitting model (linear), assessed with root mean square error (RMSE), suggested that 33.3% (20.6%–44.1%) of mangrove area was lost over the past 50 years (Figure 4). The ecosystem therefore meets the category threshold for Vulnerable (range: Least Concern–Vulnerable) under Criterion A1 (Table 2).

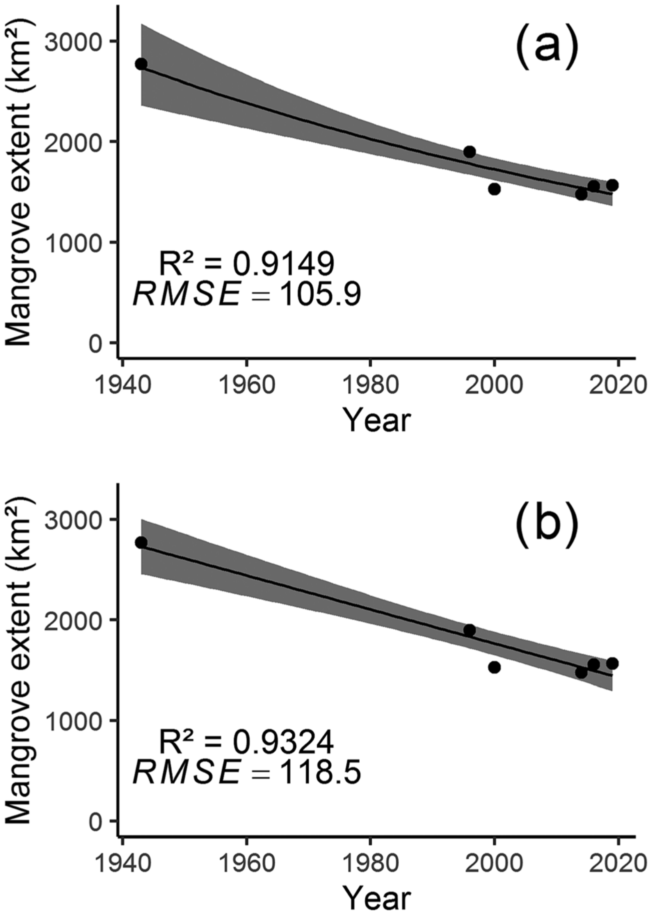

FIGURE 4 Estimated area of Rakhine mangroves estimated based on (a) a fitted exponential model ($n = 6$) and (b) a linear model ($n = 6$), with 95% confidence intervals shaded in dark grey. Area estimates are based on the Army Map Services for Burma, Global Mangrove map for 2000 from Giri et al. (2011), Global Mangrove Watch maps for 1996 and 2016 and a classified map based on Landsat 8 for the 2019 dry season. RMSE, root mean square error.

3.1.2 | Criterion A2b

Two approaches were used.

- GMW data (1996–2016): When estimating recent changes in mangrove area, an exponential model returned a smaller RMSE than a linear model (Figure S5), so the exponential model was used to extrapolate predicted mangrove loss to 2046. The analysis showed that the estimated mangrove area declined from 2230 km^2 in 1996 to 1857 km^2 in 2016 (Figure S5). This model estimated that 36.5% of mangroves will be lost by 2046, with an upper bound of 45.8% and a lower bound of 25.4%. With these estimates, the ecosystem meets the criteria for Vulnerable (range: Least Concern–Vulnerable) under Criterion A2b (Table 2).
- Landsat dense time series: The classification model applied to the 1132 Landsat mosaics achieved an overall accuracy of 95.8%, with the mangrove class having a user's accuracy of 92.5% and producer's accuracy of 72.3% (Table 3).

The GAMM with the best fit included cloud cover, time and day of year all as non-linear explanatory variables. It also included the satellite sensor as a random effect, a variance structure controlled by the proportion of the mosaic that is cloud free and a temporal correlation structure of 0.2 between each consecutive time step (Figure 5; additional information on model selection in the Supporting Information). When the model results are extrapolated to 2038, a best estimate of 35.8% of mangrove extent will be lost using an absolute rate of decline, while 33.4% of mangrove extent will be lost using a proportional rate of decline (Figure 6a; Bland et al., 2017). Under the worst case scenario, 73.3% of mangrove extent will be lost using an absolute rate of decline, while 62.8% of mangrove extent will be lost using a proportional rate of decline (Figure 6b). Based on these results, the ecosystem meets the criteria for Vulnerable (Least Concern–Endangered) under Criterion A2b (Table 2).

TABLE 2 Results for the Red List of Ecosystems assessment for all sub-criteria for Rakhine mangroves.

Criterion	Declining distribution (A)	Restricted distribution (B)	Environmental degradation (C)	Biotic disruption (D)	Quantitative risk analysis (E)	Overall ecosystem status
Sub-criterion 1	VU (LC–VU)	LC	NE	DD	NE	CR (VU–CR)
Sub-criterion 2a	NE	LC	LC[b]	NE		
Sub-criterion 2b	VU (LC–VU) VU (LC–EN)		NE	LC–VU[b]		
Sub-criterion 3	CR (VU–CR)[a] EN (VU–EN)	LC	NE	LC–VU		

Note: Categories in brackets indicate plausible bounds. Two approaches were used to assess each of Criteria A2b and A3; both are reported.
Abbreviations: CR, critically endangered; DD, data deficient; EN, endangered; LC, least concern; NE, not evaluated; VU, vulnerable.
[a]Sub-criterion 1 assesses a criterion over the past 50 years; Sub-criterion 2a assesses a criterion over the next 50 years; Sub-criterion 2b assesses a criterion over any 50-year period, including the past, present and future; Sub-criterion 3 assesses a criterion's historical change since approximately 1750.
[b]Results from Murray et al. (2020).

TABLE 3 Error matrix of the dense time-series classification model based on stratified random sampling with proportional allocation.

	Mangrove	Not mangrove	Total (Wi)	User's accuracy (%)
Mangrove	0.091	0.007	0.098	92.5
Not mangrove	0.035	0.867	0.902	96.1
Total	0.126	0.874	1	
Producer's accuracy (%)	72.3	99.2		Overall accuracy: 95.8%

Note: Cell entries represent the proportion of the area. Mapped categories are in rows while the reference categories are in columns.

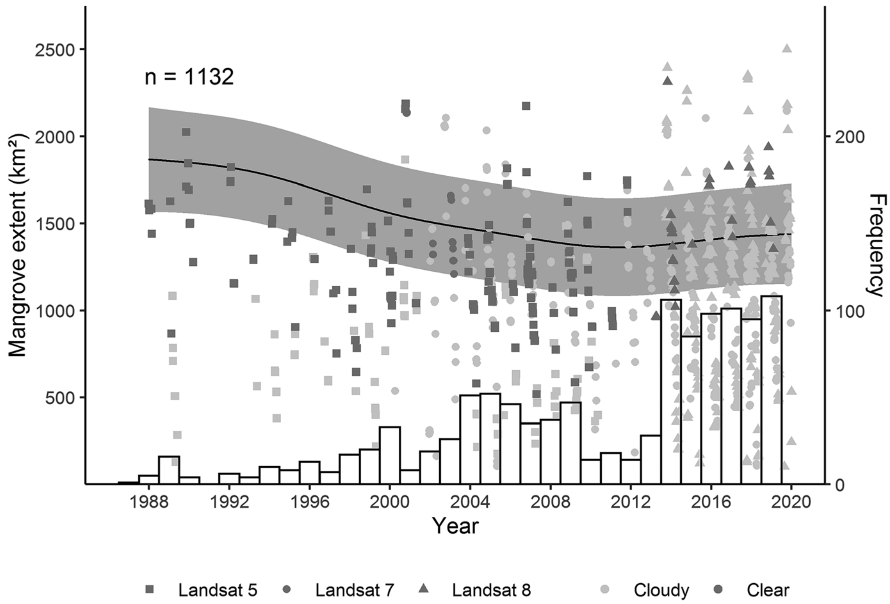

FIGURE 5 Mangrove extent for Rakhine mangroves estimated by the generalized additive mixed model (GAMM), with 95% confidence intervals shaded in grey. Symbols represent the satellite that captured each data point. Darker symbols represent images with <20% cloud cover. The histogram at the bottom shows the number of satellite images available at 2-year intervals.

3.1.3 | Criterion A3

Based on Storey (2015), only an estimated 6% of the historical (1750s) mangrove extent at Rakhine remained in 2015. The second analysis, combining the data from the collated maps (Section 2.2.1) and assuming a linear rate of decline, estimated that 82.5% of historical mangrove extent has been lost under the worst case scenario, 62.7% has been lost under the best case scenario, with the best estimate of 77.0% historical mangrove extent lost since 1750. Without additional information that can reduce this uncertainty further, these results were combined, following the precautionary principle and keeping the best estimate from the previous assessment (and a higher risk category), returning a status of Critically Endangered under Criterion A3 (range: Vulnerable–Critically Endangered), highlighting the high degree of uncertainty that remained (Table 2).

3.2 | Criterion B

The EOO of Rakhine mangroves was 54,874 km^2. AOO was estimated as 246 10 $\times$ 10 km grid cells. Additionally, there is evidence of an ongoing decline in ecosystem extent, thus fulfilling Sub-criteria a and b required to list the ecosystem under Criteria B1 and B2. Based on these results, the ecosystem meets the criteria for Least Concern under Criteria B1 and B2 (Table 2).

3.3 | Criterion C

Based on the sea-level rise model by Lovelock et al. (2015), under an extreme scenario of 1.4-m relative sea-level rise in the region, 2.3% of the mangrove area is predicted to be lost by 2100. However, it is important to note the limitations of the model by Lovelock et al. (2015). First, it did not account for mangrove plasticity or adaptation and therefore may overestimate ecosystem risk as mangroves have been shown to be resilient to sea-level rise (Duncan et al., 2018). On the other hand, the low relative sea-level rise projected by the model is due to a high concentration of total suspended matter in the water column in the region, though river dams may reduce this in the future, potentially leading to faster rates of sea-level rise.

Regardless of these uncertainties, the overall estimated mangrove area loss is very low, and with this estimated level of relative sea-level rise, along with the assumption that this leads to a relative severity of >80% due to mangrove drowning, the ecosystem is assessed as Least Concern under Criterion C2a (Table 2).

3.4 | Criterion D

Two results were used to assess Rakhine mangroves under Criterion D. First, Worthington and Spalding (2018) concluded that 30.4% of Rakhine mangroves will become degraded by 2050 when using the

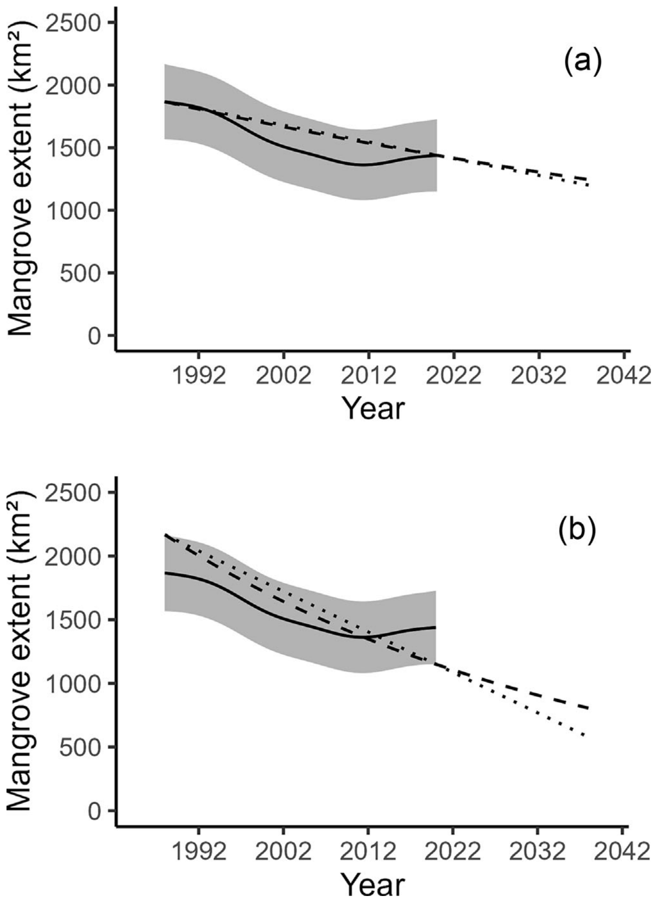

FIGURE 6 Predicted mangrove extent estimate in 2038 based on the absolute rate of decline (dotted line) and proportion rate of decline (dashed line), assuming (a) best estimate and (b) worst case scenarios.

year 2000 as a baseline. The ecosystem was assessed as between Least Concern and Vulnerable under Criterion D2b (Table 2), depending on assumptions about the relative severity of degradation.

Second, based on the developed mangrove degradation model, 49.4% (Standard Error [SE] 1.2) of Rakhine mangroves were mapped as degraded in 2014 and 49.6% (SE 1.1) in 2019 (Figure 7). Spatially, degradation can be observed throughout the ecosystem. The Wunbaik reserved forest was an exception within the ecosystem, remaining as relatively intact mangroves though some degradation can be observed along the edge of the forest reserve (Figure 7).

The 2014 and 2019 models had overall accuracies of 84.4% and 88.4%, respectively (Table 4). Based on the observed severity of degradation of the training points, pixels classified as degraded were assumed to have a plausible relative severity range from 50% to 99%. If a historical baseline is used, assuming none of the ecosystem was degraded in the 1750s, the ecosystem is classified as Least Concern if the relative severity of the mapped degradation is less than 90%. However, if a relative severity greater than 90% is used instead, the ecosystem is classified as Vulnerable under Criterion D3 (Table 2; Figure 8).

4 | DISCUSSION

Mangrove loss in Myanmar has been well documented over the years (De Alban et al., 2020; Murray et al., 2020; Veettil et al., 2018). While the focused reassessment of Myanmar's coastal ecosystem, 'Rakhine mangrove forest on mud', concluded that the ecosystem should remain classified as Critically Endangered due to extensive historical loss, the use of several new methods demonstrated a range of novel uses for remote sensing for assessing risks to mangrove ecosystems.

The importance of mangrove ecosystems has been recognized as a global priority for conservation (Friess et al., 2020). Despite this, Myanmar remains one of the countries with the highest rates of mangrove loss, with much of that degradation focused on the Rakhine coastline. In Rakhine, mangroves provide essential ecosystem services for the people living here by helping reduce the impacts of tropical cyclones affecting the area; acting as the main source of fuel and energy for the local people; providing vital fish, crab and shellfish nurseries; and sequestering and storing carbon (Storey, 2015; Zöckler & Aung, 2019). The assessment highlighted that the ecosystem continues to be threatened and has a high risk of collapse without conservation interventions to reduce ecosystem degradation and land conversion as a result of expanding agriculture and aquaculture and overexploitation of mangrove trees for firewood and timber (Zöckler & Aung, 2019). Despite this high risk of ecosystem collapse, the results also show that the rate of recent mangrove area loss may be slowing in the past two to three decades, with the results echoing a recent assessment conducted for the neighbouring Indian Sundarbans mangroves where they also reported reduced rates of loss (Sievers et al., 2020). Along with a reduced rate of mangrove loss in recent years, the Wunbaik reserved forest remained a region with relatively intact mangroves compared to the rest of the ecosystem, though some degradation was still observed here, particularly along the edge of the forest reserve. This suggests that while the protected area managed to offer protection to the mangroves by limiting direct mangrove deforestation, recent developments have led to increased encroachment of degradation into the forest reserve from surrounding areas. Stronger enforcement, such as reducing the surrounding shrimp farms and restricting their further expansion or reducing woodcutting by locals (Saw & Kanzaki, 2015), will thus be required in the near future to ensure the continued maintenance and survival of the mangrove ecosystem in this area. It is important to acknowledge that ongoing political and social unrest in Myanmar and Rakhine may force more people into poverty and dependency on unsustainable harvesting and agricultural practices (Ware, 2015). Mangrove conservation in Rakhine will require a combination of socio-economic solutions aiding the people here, sustainable use of mangroves, national land use policies that take into account the increasing population in the region, increased protection of the remaining intact mangrove forests by reducing and restricting shrimp farm development and potential plans to restore degraded mangroves through rehabilitation of abandoned shrimp ponds (Maung & Sasaki, 2020; Oo, 2002; Veettil et al., 2018).

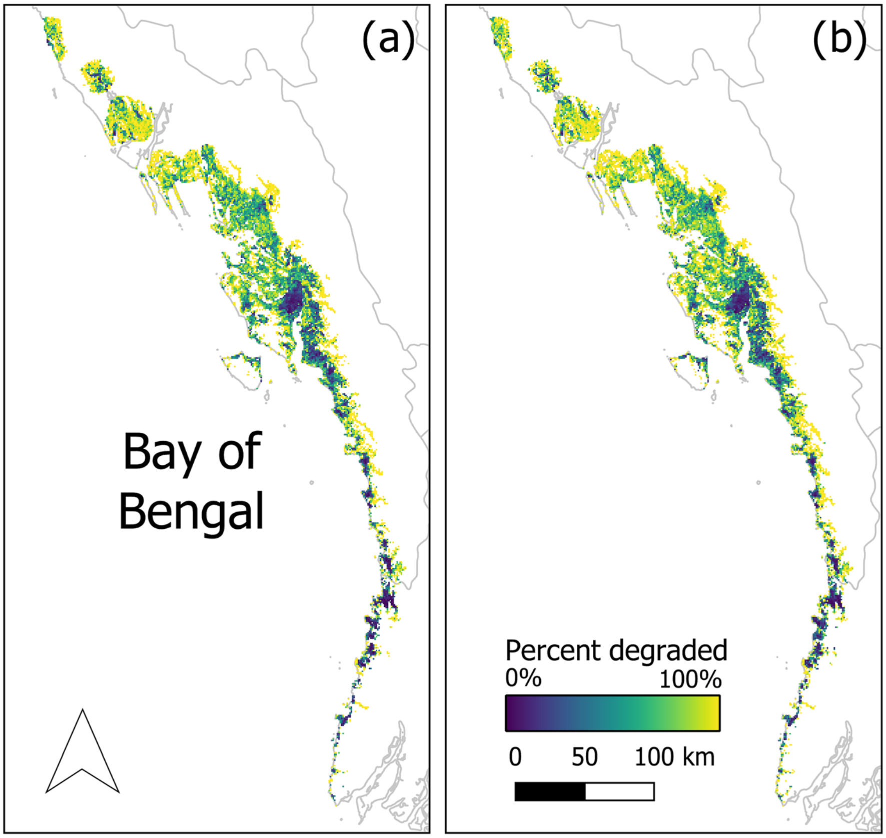

FIGURE 7 Spatial summary of degradation of Rakhine mangroves, showing the percentage of 1 × 1 km grid cells classified as degraded in (a) 2014 and (b) 2019.

TABLE 4 Error matrix of the Rakhine mangroves' degradation models.

	Degraded	Intact	User's accuracy
2014			
Degraded	41.9%	8.1%	83.8%
Intact	7.5%	42.5%	85.0%
Producer's accuracy	84.9%	84.0%	Overall accuracy: 84.4%
2019			
Degraded	45.4%	7.4%	85.9%
Intact	4.2%	42.9%	91.1%
Producer's accuracy	91.5%	85.2%	Overall accuracy: 88.4%

Note: Cell entries represent the percentage of the total area. Map categories are in rows while the reference categories are in columns.

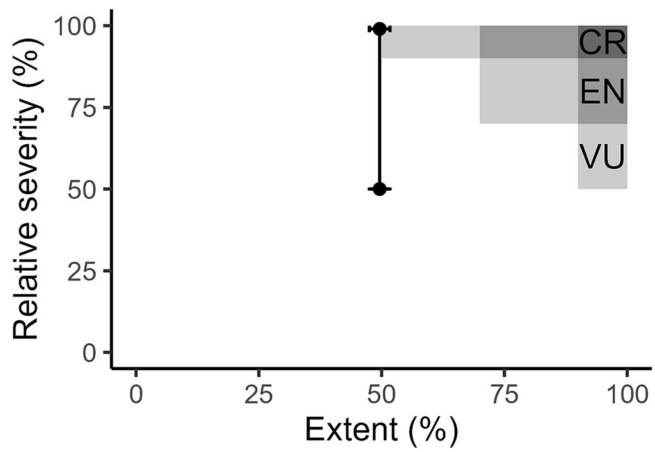

FIGURE 8 Plausible bounds for the extent of Rakhine mangroves' degradation and relative severities under Criterion D3. CR, critically endangered; EN, endangered; VU, vulnerable.

Previous research has shown the importance of reassessments for ecosystems and species (Cazalis et al., 2022); >750 species had their Red List of Threatened Species status changed between 2019 and 2020 alone (IUCN, 2020). The reassessment of Rakhine mangroves provided a more complete analysis of its risk of collapse by incorporating additional lines of evidence (Bland et al., 2017) and highlighted several sources of uncertainty that can be minimized and quantitatively reported with satellite remote sensing methods. Using a dense time-series of satellite imagery to classify ecosystem areal change over 30 years allows non-linear trends and quantitative uncertainty to be modelled that would otherwise be impossible to present or be reported (Foody, 2010; Lee et al., 2021), and using an explicit ecosystem conceptual model developed for this ecosystem allows clear specification of the potential drivers of ecosystem degradation here (Lee et al., 2021).

Despite this, uncertainty in the assessment outcome remained, particularly with regard to the historical area change of the ecosystem, as there are multiple estimates of the ecosystem's historical extent that are impossible to verify. Both estimates included important assumptions that were unlikely to be met. The data from Storey (2015) were estimates based on interviews with villagers in Northern Rakhine, where the most extensive mangrove degradation was observed, suggesting that relying on these estimates may overestimate mangrove loss if extrapolated to the entire ecosystem. The alternative estimate of historical mangrove extent was based on linear back-extrapolation to more than 200 years ago from 80 years of data. This required an assumption that there has been a constant rate of deforestation over 250 years, as additional information on the shape of the trajectory is not available, which is extremely unlikely (Armenteras et al., 2017). Assessing trends in ecosystem areas over the past 250 years, as required by the Red List guidelines, will likely be challenging for many assessments. The AMS maps from the 1940s were used as the earliest available data available to reduce uncertainty, but a 170-year period without data still exists. To produce more reliable estimates, physical and biological factors known to explain land use and deforestation patterns can be used to parameterize deforestation models (Brown et al., 2007), or distribution models with environmental variables to estimate the expected distribution of the ecosystem in the absence of anthropogenic effects can produce other points of comparison (Keith et al., 2013). Ultimately, avenues to reduce the uncertainty of estimating area trend over such a long period of time was pursued within this study, and while some uncertainty remained due to data paucity, an outcome of *Critically Endangered* remained as the Red List suggests reporting the highest risk category reached based on the precautionary principle (Bland et al., 2017).

With the continued development of satellite data and methods to analyse data, there are still gaps that can be filled for more complete Red List assessments. For example, Landsat satellites provided continuous data beginning 30 years ago, allowing for statistical modelling of ecosystem extent, which is otherwise impossible. As time goes on, more satellite data will be collected to fill the 50-year time frame required by the Red List, further reducing the need for extrapolation and the uncertainty of the results. Additionally, data at higher spatial and temporal resolution than Landsat, such as the PlanetScope constellation of satellites (Planet Team, 2017), can be added as additional sources of information as they become more readily available. For example, PlanetScope data are able to accurately characterize forest phenology at the tree-crown scale (Wu et al., 2021), an important indicator signalling ecosystem change under climate change (Ettinger et al., 2022). Historical satellite or aerial photography that is being declassified offers another opportunity for providing long time-series data to track historical ecosystem change (Nita et al., 2018), similar to how the US AMS data were used in this study. However, while historical imagery is an irreplaceable source of ecosystem information, it is also difficult to assess the accuracy of these maps due to their age, and it must be used with caution.

Using a dense time-series model to estimate ecosystem extent trends enables the full use of the information available from regularly collected satellite imagery. While attempts to assess the accuracy of the dense time-series classification maps (Table 3) were made, these relied on creating validation points where pixels were assumed to be either always mangroves or never mangroves. Unfortunately, this means that pixels where mangrove gain or loss occurred were not assessed, and it is likely that these pixels are also more prone to misclassification. Regardless, the best available data and methods were used here to produce a quantitative estimate of ecosystem area trends, which is invaluable for producing informative risk assessments with significance testing.

While remote sensing offers unique opportunities to tracking ecosystem change, it is important to note that the analyses that were done for the reassessment did not include additional field data. When estimating ecosystem degradation, the lack of field data limited the results to only two possible classes of degradation. This method also quantified mangrove degradation into a single, relatively simple indicator despite the many contributing factors that can drive and represent degradation (Yando et al., 2021; Figure 3). Quantitative field measurements of environmental and biotic degradation will be needed to estimate a continuous metric for the relative severity of ecosystem degradation as required by the Red List. Furthermore, combining the mangrove conceptual model with a more conceptualized degradation framework based on field data will allow us to paint a more holistic picture of the entire mangrove ecosystem, its status and the threats that may affect it.

The results from this study highlight the benefits of incorporating new data and methods that are released and developed to conduct detailed, strategic reassessments of ecosystem risk. Not only will this improve the accuracy of the risk assessments and fill previously existing knowledge gaps, it can also identify further data and methodological gaps to help guide future research. A template for future mangrove Red Lists using satellite data is presented here. As the Red List of Ecosystems continues to increase in prominence, reassessments encourage assessors to consider the latest data and methods available, ensuring the results are based on the most up-to-date information available.

5 | CONSERVATION IMPLICATIONS

By extending the assessment of the 'Rakhine mangrove forest on mud' with additional data and analyses, some of the uncertainties involved in the first assessment were reduced. Uncertainty regarding the historical change (since 1750) in ecosystem area remained, and the ecosystem is still assessed as Critically Endangered (with a plausible range between Vulnerable and Critically Endangered) to follow the precautionary principle where the overall status of the ecosystem is the highest risk category obtained (Bland et al., 2017). While there is evidence that recent rates of mangrove losses are slowing, coinciding with the reducing rates of mangrove deforestation observed globally (Hamilton & Casey, 2016), this could be due to the small amount of mangroves remaining, meaning there is less left to be cleared. Successful recovery and restoration of the ecosystem to a lower risk level will require increasing the current coverage of mangrove area back towards the historical extent of the ecosystem (at least 10% of its historical distribution in the 1750s).

In addition to areal loss, there is also considerable mangrove degradation observed, including around and within protected areas. Within the existing remaining mangrove forests, degradation can lead to declining ecosystem quality (Yando et al., 2021), and Rakhine mangroves will still be classified as Vulnerable even in the absence of the observed mangrove loss. This indicates that the establishment of additional protected areas alone may not be sufficient to protect the ecosystem. For example, the Wunbaik reserved forest is one of the largest remaining protected mangrove forests in the region but is suffering from degradation due to expansion of paddy fields and shrimp ponds, along with illegal woodcutting by locals (Saw & Kanzaki, 2015), a situation similar to the neighbouring Sundarbans (Roy, 2016). To address the issue of increased mangrove exploitation, multiple key points need to be addressed and solved. The main incentive identified for locals to switch from less damaging subsistence fishing to more destructive shrimp farming is to improve their financial situation, as no alternatives are currently available to them (Saw & Kanzaki, 2015). Thus, alternative financial incentives and sources of income and livelihoods for the locals will need to be developed and enhanced as a means of mangrove conservation. Moreover, improving local participation in mangrove management has been shown to be effective in reducing long-term conflicts between local communities and the government agencies in charge of management, improving local resilience to sudden disasters and participants' livelihoods and imparting a sense of security and community (Islam et al., 2013). Lastly, restoration of abandoned shrimp ponds also provides an opportunity to improve the overall status of the ecosystem, reducing degradation. This is already occurring naturally in some areas (Maung & Sasaki, 2020), though further investments can potentially lead to further, more targeted mangrove recovery and become a source of income for the local communities (Damastuti & de Groot, 2017). Successful mangrove restoration is an ongoing challenge that requires more than just planting mangroves, and the proper allocation of resources is essential to ensure local support. Mechanisms that are fair and equitable, providing a potential source of income to the local communities through sustainable mangrove use, are needed to ensure the long-term sustainability of the mangrove ecosystem and the people that reside next to it (Lovelock & Brown, 2019).

AUTHOR CONTRIBUTIONS

Calvin K. F. Lee: Conceptualization; methodology; visualization; writing—review and editing; writing—original draft; validation; formal analysis. **Emily Nicholson**: Conceptualization; supervision; project administration; writing—review and editing; funding acquisition. **Clare Duncan**: Conceptualization; writing—review and editing; supervision; methodology. **Hedley S. Grantham**: Writing—review and editing. **David A. Keith**: Writing—review and editing; conceptualization. **Rob Tizard**: Writing—review and editing. **Nicholas J. Murray**: Writing—review and editing; methodology; conceptualization; supervision.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

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

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SUPPORTING INFORMATION

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