Spatiotemporal pattern of forest degradation and loss of ecosystem function associated with Rohingya influx: a geospatial approach

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Abstract

Violence in Rakhine, Myanmar forcibly displaced nearly one million Rohingya who took refuge in Cox's Bazar–Teknaf peninsula of Bangladesh. Initially, nearly 2,000 ha of forested lands had to be cleared to accommodate them in an area, that is ecologically very sensitive. Fuelwood collection and illegal logging have become widespread since their arrival, causing severe environmental degradation, including loss of a vast amount of forest cover. To devise conservation strategies of a highly sensitive ecosystem, it is imperative to understand the degree of forest cover deterioration and associated impacts related to Rohingya emigration. This study employed satellite images to monitor and model spatiotemporal pattern of forest cover degradation, and loss of ecosystem function in the peninsula. Supervised classification method was used to derive multidate land use/cover data which was then utilized to monitor spatiotemporal pattern of forest cover change from 2017–2019. Dynamic modelling was performed to predict changes in the forest covers using markov cellular automata. Analysis revealed that 3,130 ha of different forested covers were transformed into either refugee camps or degraded forest cover between 2017 and 2019. Prediction showed that around 5,115 ha of forest may experience loss from 2019–2027. Furthermore, above ground biomass and carbon stock estimation indicated a consistent loss, which is likely to swell if present rate of deforestation continues. The findings of this work have considerable implications in developing conservation decisions, priority interventions and public policies to save an ecologically sensitive area.

1. Introduction

Globally, forcibly displaced population reached remarkably high from 43.3 m in 2009 to 70.8 m in 2018, largely because of persecution, conflict, violence or human rights violations (UNHCR, 2019). Presence of displaced people may introduce a range of effects to the host environment of which deforestation, land degradation and impacts on water supply and quality are noteworthy (Black, 1994). However, severe pressure on local environment causes forest cover to deplete substantially (Hagenlocher et al. 2012; Birendra and Nagata, 2006) due to enhanced competition for natural resources between displaced communities and local population (Chambers, 1986). Furthermore, clearing of forest cover evidently reduces ecosystem functions and services (Foley et al. 2007). For instance, biomass and carbon stock depletion in relation to deforestation caused by increased human activities can accelerate climatic change at regional and local scales (Panja, 2020; Bonan, 2008; Malhi et al. 2002).

Following severe violence in Myanmar's Rakhine State in 2017, nearly a million forcibly displaced Rohingya population (a minority ethnic group) took refuge in Cox's Bazar– Teknaf peninsula of Bangladesh (UNHCR, 2017), which is believed to be the largest refugee camp in the world at present (Kolstad, 2018; IOM, 2017). Although Rohingya issue dated back in 1942 (Human Rights Watch, 2000), their influx is multiplied since August 2017 (UNOCHA, 2018). A total of 932,940 Rohingya are now being hosted in 48 temporary camps which are located either within the reserve forests or in a close proximity to forested lands (UNDP Bangladesh and UN WOMEN Bangladesh, 2018). Since Cox's Bazar– Teknaf peninsula is an ecologically critical area (ECA) (DOE, 2015), hosting such a big number of refugee population is not only a significant threat to the environment (Hassan et al. 2018; Rahman, 2017) but also has implication for local and regional security (Bashar, 2018; Rahman, 2010). Forest clearance for building camps and ensuring livelihood activities (Lynch, 2002; Rashid et al. 2020), especially within 15 km of the camps (Sato et al., 2000), are two major issues that the peninsula is currently facing. Although the Rohingya communities are supported by different organizations, these supports do not guarantee cash flow, hence they have no or limited livelihood options (IOM and FAO, 2017). Therefore, they depend on available forest resources to maintain their livelihoods (Wilson, 1994; GTZ, 1994), which is posing a significant threat to forest resources (Ghimere, 1996). Besides, cooking requires fuelwood (IOM and FAO, 2017) which is being met up through harvesting from locally available natural and community forests. Since refugees use natural resources in a more unsustainable way than local communities (Black and Sessay, 1998), long– term impacts on natural resources could be irreversible.

Various impacts associated with forced displacement on host environment are noted in a number of studies (see Hagenlocher et al. 2012; Black, 1994), however the extent of ecosystem degradation depends on factors like destination country's capacity (Hugo, 1996), degree of disturbance to forests (Shukla et al. 2011) and institutional arrangement (Black and Sessay, 1998). Since Bangladesh is densely populated and have limited natural resources, particularly forested lands, sheltering nearly one million Rohingya over the peninsula resulted in a variety of impacts, including severe depletion of forest covers (Ahmed et al. 2019). As best management practice requires information about spatiotemporal pattern of the past, present and future scenarios of a geographic phenomenon (e.g., forest ecosystem), monitoring and predicting forest extent in the peninsula with satellite data could be of great value (Bjorgo, 2000a; Lodhi et al. 1998). Although geospatial data are valuable source of information for crisis and disaster management, relatively little is done in elucidating degradation of natural forest and related ecosystem function in response to a sudden humanitarian crisis such as Rohingya. This work aims to fill this void. Despite a couple of works attempted to estimate forest loss (Ahmed et al. 2019; Hassan et al., 2018), they are however limited in data and scope. Notably, they are unable to show factors accountable for forest degradation, prediction of forest degradation (assuming business– as– usual scenario), and most importantly, loss of ecosystem function over space and time. Planning and efficient management of meagre natural resources requires up– to– date data, therefore, availability of existing forest resources and potential loss in relation to refugee migration is expected to provide crucial information to managers and policymakers (Morales-Hidalgo, 2015; Romijn et al., 2015; Bouchardy, 1995; Bjørgo, 1999). This work, thus, attempts to answer two research questions: (i) what is the extent of forest degradation in environmentally sensitive Cox's Bazar– Teknaf peninsula in response to Rohingya influx; and (ii) what is (would) be the degree of ecosystem function loss, at present and in the future, under multiple stressors and stimulus, if Rohingya issue persists.

2. Materials and methods

2.1 Description of the study area

The peninsula is located in Cox's Bazar, a southeastern most district of Bangladesh. As this study focuses on the impact of Rohingya on forest degradation and ecosystem function loss, it considers administrative boundaries of Bangladesh Forest Department (BFD). In Cox's Bazar district, there are two forest divisions, i.e., north and south, however refugee camps are mostly built in South division (BFD GIS Database). Based on influx of Rohingya and their catchment area, this study takes 23 beats into account (beat is the smallest forest administrative unit, defined by BFD) of south forest division. To understand future condition of forest cover, we further consider some portion of the Naikhongchari beat of Bandarban forest division defined by IOM and FAO (2017). The use of beat may be beneficial to investigate future impact of refugee in every direction from existing camps. There are three sub-districts (*upazilas*) and 24 beats within the study area (Fig. 1). Geographically, it is located between 92° 17' E, 20° 50' N and 92° 12' E, 21° 19' N, and covers an area of 41,162 ha.

Irrespective of administrative boundaries, defined by BFD and Bangladesh Bureau of Statistics (BBS), environmentally, the study area situated in a very sensitive ecosystem. It includes Teknaf Wildlife Sanctuary (TWS) (GoB, 2009; BFD, 2014) formerly known as the Teknaf Game Reserve (TGR) (Alam et al. 2012). Besides, it has proposed Inani National Park (Nishorgo, 2019), which is a reserve forest (Belal, 2013; Rahman, 2011). The area of the TWS is 11,615 ha (Green, 1987; Nishorgo, 2019, Moslehuddin et al., 2018), covering 25% of the study area, and situated in close proximity to Rohingya camps. Inani Reserve Forest has an area of 15,500 ha, covering 33% of our study area. The other reserve forest comprises an area of 6,365 ha, which covers 13.5% of the study area. Therefore, 71% of the study area includes a critical ecosystem and the rest (29%) is no– forested land, occupied by human settlements and agricultural lands. As a tropical semi– evergreen forest, the area is home to a wide variety of flora and fauna, including 55 mammals, around 280 birds, 56 reptiles, 13 amphibians and 290 plant species (Khan, 2008; Nishorgo, 2019). The study area also serves as a key habitat to critically endangered flagship species of Asian Elephants (*Elephus Maximus*) (Khan, 2015). It is characterized by hot and humid climatic conditions, and therefore, conducive for a range of biodiversity (Butler, 2012). Prior to recent influx, Rohingya communities are living in two camps since 1942 (Fig. 1) (Human Rights Watch, 2000) within the study area. After 25$^{\mathrm{th}}$ of August 2017, with a massive influx, they are now located in 48 camps. The density of Rohingya population is shown in Fig. 1.

2.2 Data acquisition and preparation

This study considers both spatial and non– spatial data and they have been acquired from a variety of sources (Table 1). Satellite data includes Sentinel 2A, RapidEye, World View– 2, multi– date UAV and a digital elevation model from Shuttle Radar Topographic Missing (SRTM). Sentinel images represent winter season and pre– and post– influx of Rohingya situations. Vector data includes administrative boundary and location of camps, obtained from Survey of Bangladesh (SoB), BFD and UNHCR. In addition, human trails are derived from the UAVs and Google Earth imageries and population data of each camp was obtained from FCN– UNHCR and NPM– IOM. In addition, a field survey was conducted in February 2018 to understand state of the environmental condition. Observational technique along with photographic method was accepted, during the field works, to support satellite– based evaluation of forest function loss in the study area.

Sentinel 2A imageries are first geometrically corrected and a root mean square error (RMSE) of <1 pixel is accepted. Atmospheric correction is then carried out with SEN2COR toolkit to convert Top of Atmosphere (TOA) value to surface reflectance (Cleverset et al., 2017; Quintano et al., 2018). A Universal Transverse Mercator (UTM) system with 46N is used to project spatial datasets and then clipped to the study area boundary.

2.3 Image classification and accuracy assessment

A modified version of the Anderson level 1 land use and land cover (hereinafter, LULC) classification scheme (Anderson et al., 1976) is used to classify Sentinel data into discrete LULC categories (Table 2). A hybrid approach, comprising unsupervised and supervised techniques, is employed (Bauer et al., 1994). First of all, an Iterative Self– Organizing Data Analysis (ISODATA) algorithm is used to derive signatures from multitemporal Sentinel data, pertaining to the study area. The signatures were then evaluated using histogram and transform divergence (TD) techniques to ensure normality (Yuan et al., 2005). The TD value of [?] 1900 is accepted in this work. Besides, reference data (e.g., RapidEye, World View– 2 and Google Earth Images) for each year is considered, side– by– side, in an image processing system to determine the usefulness of individual signatures. This process helps isolating signatures that are suitable for classifying images. A maximum likelihood routine is subsequently applied to derive distinct LULC categories (Bolstad & Lillesand, 1991). Since the study area has diverse land covers, misclassification of pixels is noticed between shrubs and agriculture, mixed forest, and canopy trees and homestead vegetation cover. To subdue issues with misclassification, post– classification refinement is carried out to recode mixed pixels into correct LULC categories (Harris & Ventura, 1995). Finally, three maps of the study area are obtained, representing LULC data of 2017, 2018 and 2019.

To evaluate classification accuracy, 100 points for each LULC classes are derived from high resolution images, noted above (Table 1), with a stratified random sampling technique. Using reference data and classified images, an error matrix is then prepared from which four accuracy metrices (e.g., overall, producers, user's accuracies and kappa statistics) are computed.

2.4 LULC change detection and analysis of spatial trend

A post– classification change detection technique is used to determine changes in LULC categories between 2017 and 2019. This process resulted in three change detection maps; (i) 2017– 2018; (ii) 2018– 2019; and (iii) 2017– 2019. These operation helps defining changes in LULC which subsequently aid in assessing forest degradation, caused by resettlement of Rohingya populations. Earlier (e.g., 2017) and later (e.g., 2018) thematic maps are compared, on a pixel– by– pixel basis, and transformation of LULC categories is defined to compute changes from a specific land class to other classes (e.g., shrubs to Rohingya camps). The spatial trend is then analyzed, based on the pattern of change between earlier and later periods. Third order polynomial equation is used to analyze the spatial change pattern. The resulting trend surfaces aid understanding the direction of LULC change.

2.5 Prediction of LULC change

Based on the classified maps, this study also attempts to predict LULC for 2023 and 2027. Three steps are involved in the prediction process. They are estimation of transition probabilities, creation of transition suitability maps and finally predicting LULC. A combination of Markov chain with cellular automata (CA) method is employed as former technique is unable to provide spatial dimension of a phenomenon. To simulate future land covers, actual data of 2017– 2018 are used to predict 2019 LULC which is then compared with observed data of 2019 to check the effectiveness of model.

Transition probability matrix is derived through markov module as a first step. LULC thematic maps of different periods are inputted to estimate transition probabilities (Pijanowski et al., 2002). A suitability map for each of LULC class defines transformation suitability of a certain class from all other categories (Halmy et al., 2015). Stressor and stimulus parameters are, therefore, required to develop suitability map to account dynamic aspect of land cover change. In this work, forest degradation is based on both stressor and stimulus parameters. Stimulus variable includes number of Rohingya population, stressor parameter comprises high elevation, and constraint is defined by highly protected areas. The stressor, constraint and stimulus variables are determined on the basis of previous studies (e.g., IOM and FAO, 2017; IUCN Bangladesh, 2018), 2018 field works and local knowledge of the sites (Table 3). Since not all LULC classes are subject to change rapidly, six dynamic (Table 3) and one constraint variables are included to isolate suitable locations or forest patches that could be degraded under the influence of refugee occupancy.

As degradation of forest is accelerated by fuelwood collection and illegal logging by the Rohingya communities, distribution of Rohingya population is a key factor for a suitability map. Apart from population variable, four distance variables (Table 3) are also considered. Due to the fact that the Rohingya can travel up to 16 km (IOM and FAO, 2017), and on average, 7 km to collect forest resources, a 7– km buffer is constructed using center of each refugee camps. These buffers are then intersected with population distribution to identify number of people that can conceivably influence forest degradation. In other words, if a forest area is within a distance of 7– km buffer of three camps (C1, C2 and C3) and these camps contain 100, 200 and 150 people, then a particular forest cover has a total of 450 humans. These populations are considered as potentially degraders. The results are subsequently aggregated to a 100x100 m grid based on which a ranking is performed. This helps determining forest covers subject to degradation due to existence of the Rohingya communities. The higher the population in each grid, the greater the likelihood of a forest to be degraded. In the creation of forest degradation suitability maps, maximum weighting (0.5) is assigned to population field whereas other parameters receive rest of the weights (0.5), using a scale of 0-1. A weighted linear combination method is then employed to develop transition suitability maps.

The transition probability or transition suitability maps of 2017– 2019 are considered, wherein 2019 LULC is used as base. Since CA Markov provides spatial distribution of LULC change, area of each class to be changed to other classes are determined by transition potential or transition suitable maps (Halmy et al., 2015). These transition areas are divided by the number of time periods in the simulation (1, 4 and 8 in this case). This operation provided areas to be converted to another LULC class. The CA Markov with these principles results predicted LULC data which are then assessed for accuracy by considering kappa index of agreement and disagreement. LULC prediction for the year of 2023 and 2027 are conducted, based on actual data of 2019 (Pontius and Millones 2011).

2.6 Estimating above ground biomass and carbon stock

Above ground biomass (AGB) is an important function that a forested land offer, and plays an important role in the study of carbon cycle and climate change (Li et al. 2020). This indicator can be highly useful to discern quality of an ecosystem in terms of habitat condition and biodiversity hotspot (Zolkos et al. 2013). AGB and carbon stock in this work are determined, both in space and time, to understand stresses that Cox's Bazar–Teknaf forest ecosystem is experiencing due to massive influx of Rohingya. Since the study area is inaccessible as being hilly and this study is constrained by logistics, biomass data for selected forest classes are obtained from an earlier inventory (IOM and FAO, 2017). In total, 57 subplots within 15 major plots, covering a total sample area of 6.48 ha, were used to collect AGB parameters, e.g., diameter at breast height (DBH), and height for trees and saplings. Five major LULC were considered by the inventory of IOM and FAO (2017). It is important to note that four major forest covers such as shrubs, mixed forest, planted trees and canopy forest are considered in this work, due to their greatest role in regulating ecosystem function (Li et al. 2020; Panja, 2020). A 100x100 grid is used to estimate area of each four categories which is then multiplied with AGB (ha) values of the respective forest classes (viz., 2, 17,003, 2 and 180,038 kgs for shrubs, mixed forest, planted forest and canopy forest). The values are subsequently summed to get total biomass in kilogram (kg) per grid. To obtain total carbon (in kg/grid), derived biomass values are divided by two (2). A maximum of 180,038 kg AGB or 90,019 kg carbon per grid is possible, if a grid contains 100% canopy forest. In contrast, 0 kg of biomass and carbon/grid is possible, if a grid has no forest, i.e., camps.

3. Results

3.1 Spatiotemporal distribution of LULC

Fig. 2 (a– c) illustrates LULC categories, and they are useful to identify state of forest cover in the study area. Inspection of individual land use/cover categories, derived from Sentinel images, revealed pre– and post– influx situations. For example, loss of forested land was largely distributed along the Inani National Park and TWS before influx of Rohingya (Fig. 2a), however, the distribution of degraded forest, defined by poor vegetation health, increased substantially in the subsequent years (e.g., 2018 and 2019) (Fig. 2b– c).

Temporal information of LULC data over the study area showed that four land covers, viz., homestead vegetation, shrubs, mixed and canopy forests, experienced a significant decline from 2017 to 2019, and a manifold increase in two human– dominated land covers, viz., camps and degraded forest (Table 4). For instance, mixed forest cover declined from 10,593 ha in 2017 to 9,645 ha (2018) and 9,303 ha (2019), respectively. In contrast, Rohingya camps increased from 78 ha (2017) to 1,968 ha in 2019. Likewise, degraded forest increased from 1,862 ha (2017) to 3,792 ha in 2019. Further, field works demonstrated that areas nearby the camps are completely cleared, and therefore, topsoil is severely exposed (Field Survey, 2018) (Fig. 3a). Moreover, due to high demand of fuelwood, soil is dugged to uncover and pull out the plant's remnants, especially the root of trees (Fig. 3b).

The gains and losses are analyzed, which demonstrated that agricultural land decreased to about 267 ha in 2017– 2018 and 190 ha in 2018– 2019. The maximum reduction is observed in two land covers categories, shrubs and mixed forest. During 2017– 2019, shrubs reduced to about 1,495 ha and mixed forest experienced a decrease of 1,289 ha. Homestead vegetation, planted young forest and canopy forest covers also reduced (208 ha, 160 ha and 184 ha, respectively) but not in the same magnitude of shrubs and mixed forest land covers. On the other hand, degraded forest had a maximum increase of 1,929 ha followed by Rohingya camps (1,889 ha) during 2017– 2019. Because forest covers such as shrubs, mixed forest, plantation forest and canopy forest are vital components of a forest ecosystem, loss of these covers is indicative of the deterioration of the ecosystem. Hence, this finding is crucial to understand loss of individual forest covers as well as specific decline of the respective ecosystem functions.

LULC changes between years is presented in Fig. 4, which shows changes of one land cover to another. It also shows spatial trend map of 2017– 2019, suggesting that the impact of Rohingya on forested lands was higher in and around the refugee camps than locations further away. This clearly features the effect of Rohingya on the forest covers in the peninsula.

A 'from– to' analysis with a GIS function was performed (Table 5), which shows contribution of major LULC categories to camps and degraded vegetation class during 2017 to 2019. Agriculture, homestead vegetation, shrubs, mixed forest, plantation forest and canopy forest land covers contributed to the establishment of refugee camps between 2017 and 2018, when massive influx started for the first time in August 2017, however shrubs, mixed forest, plantation forest and canopy forest covers contribution reduced substantially during 2018– 2019. This possibly reflects host country's measures to protect important forested lands in the later period. On the other hand, shrubs and mixed forest contributed largest to degraded forest cover in 2017– 2018 relative to other categories. During 2018– 2019, four important forest covers (viz., shrubs, mixed, plantation forest and canopy forest) experienced greatest degradation (Table 5). For instance, loss of shrubs cover was 701 ha (i.e., converted to Rohingya camps and degraded forest covers) in 2017– 2018 which increased to a loss of 905 ha during 2018– 2019, suggesting amplified pressure of Rohingya refugee on the forest systems of the peninsula.

The analysis of forest degradation as a function of population pressure was conducted using total population of the camps and six land use/covers variables (e.g., canopy forest, mixed forest, shrubs, planted trees, degraded forest and camps) and the result is presented in Table 6. The relationship indicates that an increase of population resulted in a decrease of forested lands and positively related with Rohingya camps and degraded forest covers. In other words, degraded forest cover and camps substantially increases with an increase of human populations in the study area (Table 6). However, p– value of the correlation matrix was statistically insignificant, ranging from 0.022– 0.361 at the 95% confidence interval.

The accuracy assessment showed that overall accuracy of 2017, 2018 and 2019 LULC maps is 86.85%, 89.12% and 91.45% with corresponding kappa of 0.86%, 0.88% and 0.91%, respectively. This signifies that derived LULC information have an acceptable level of accuracy (Abdullah et al. 2019; Zhang et al. 2013). Hence, these maps are inputted to predict spatiotemporal changes in future LULC by assuming business– as– usual scenario, i.e., if the Rohingya communities continues to live in current locations.

3.2 Prediction of forest cover change

Based on population density, physiography, accessibility and other factors (Table 3) along with transition probabilities and spatial trend, this study predicts forest cover scenario for 2023 and 2027. Fig. 5 shows observed versus simulated LULC categories of 2019. The result clearly demonstrates performance of Markov– CA approach in simulating LULC. The accuracy of the prediction showed overall accuracy and kappa of 86.21% and 0.85%, suggesting a good performance of the model. However, poor simulation was achieved for landcover of mixed forest and degraded forest categories whilst best agreement was obtained for agriculture, urban, homestead vegetation categories.

Spatial pattern of land use/covers during 2023 and 2027 is shown in Fig. 6, which indicated that the distribution of degraded forest would be widespread, if Rohingya camps exist in the peninsula at the expanse of dominant land covers (e.g., shrubs, mixed forest, plantation forest and canopy forest). Specifically, shrubs land cover is expected to decline from 7,306 ha in 2019 to 5,800 and 4,871 ha in 2023 and 2027. Other land covers such as mixed forest, planted trees and canopy forest would reduce significantly as well (Table 7). Conversely, a substantial increase in degraded forest is highly likely during two years (e.g., 2023 and 2027) though a subtle increase is seen in agriculture and camp land covers (Table 7).

Forest degradation, as a function of fuelwood collection, illegal logging and other activities, was determined based on predicted LULC of 2023 and 2027. The analysis revealed that loss of forest cover would increase dramatically, if present rate of anthropogenic activities continues in the study area. Since addition of refugee is not expected due to host country's repeated denial, it is seen that shrubs, mixed forest, plantation forest and canopy forest would experience massive reduction of which loss of shrubs and mixed forest could be substantial (Table 8).

3.3 Changes in biomass and carbon stock

The spatial pattern of AGB revealed that it declined significantly due to establishment of camps to accommodate Rohingya refugee between 2017 and 2019. Fig. 7 shows that AGB decreased over space and their distribution could decline severely in the future. At temporal scale, mixed forest experienced a severe loss in biomass followed by canopy forest cover (Table 9). Since these categories play an important role in ecosystem functioning, their influence on the loss of AGB is noteworthy than shrubs and plantation forest (young trees) landcovers. It is also observed that 27,600 tons of carbon may have released to the atmosphere between 2017 and 2019 which may increase to about 71,920 tons, if deforestation continues at the current rate.

4. Discussion

Protection, conservation and sustainable management of forest resources are often challenging (Siry et al., 2003), especially for a country like Bangladesh. The forest resources of the country are already in a critical state because of a number of reasons, including high dependency of a large number of marginalized people for their livelihood (Moslehuddin et al., 2018; Byron and Arnold 1999). Supporting additional people to take refuge, as a result of violence in a neighboring country, seems to have aggravated current deforestation rate (Alam et al., 2014), particularly in an environmentally fragile ecosystem zone.

Close inspection of LULC maps (Fig. 2a) indicated the distribution of degraded forests in the study area but its extent was low, prior to influx. Although forest resources in the peninsula are primary source of livelihoods for local people (Tani and Rahman, 2018), influx of Rohingya intensified process of degradation that led to severe deforestation (Fig. 2 b– c). Loss of forest continued since then as depicted by Fig. 2 (b– c), suggesting a loss of 1600– 2200 ha in 2018 and 3200 ha in 2019. These findings are in accord with previous works (Rashid et al. 2020; Ahmed et al. 2019; Hassan et al. 2018) despite there are differences in terms of data and methods. Figure 2 (a-c) also illustrated Rohingya makeshift camps and increasing number of deforested and degraded vegetation patches, especially in close proximity to camps. A similar observation is made in Pakistan (Lodhi et al. 1998), Malawi (Babu and Hassan, 1995), Sudan (Hagenlocher et al. 2012) and Nepal (Birendra and Nagata, 2006) that deforestation increases substantially in the event of a sudden humanitarian crisis like Rohingya. Further, it is important to note that greater increase of fuelwood collection by the Rohingya communities resulted not only in clearing of forest in around the camps but also exposing top soil in the surrounding environments which can be highly detrimental. Field works as well as a previous work (Moslehudding et al., 2018) support this observation that top soil is being exposed due to pulling of remnant of trees, and such practice is albeit unhealthy for nutrient cycle of the forested ecosystem (Chen and Li, 2003).

As illegal logging and fuelwood collection are two important activities by the Rohingya communities at present, the extent of forest cover degradation is increasing over time (Table 5, Fig. 4). This type of deterioration is affecting biomass and carbon stock of the area (Table 9) which could enhance global warming (Panja, 2020). Because of forest clearance, for instance, land surface temperature (LST) of the study area increased significantly from pre– to post– influx (Rashid et al. 2020), a very influential factor that affects local climate variability (Wang et al. 2012). As release of carbon to the atmosphere could expedite global warming, additional loss of forest cover potentially can lead to change in regional climatic system (Bonan, 2008).

Since mixed forest, and canopy forest play an important role in ecosystem functioning, particularly in the study area, their influence on the loss of AGB is noteworthy than shrubs and planted young tree covers. It is also observed that 27,600 tons of carbon may have released to the atmosphere between 2017 and 2019 which may increase to about 71,920 tons in the future as showed by prediction. In addition, fragmentation of forest patches due to intensified pressure on resources can have profound impact on wildlife habitat. For example, there were two active elephant corridors within the study area, including multiple routes for their movement, prior to Rohingya influx (Motaleb and Ahmed, 2016). Widespread fragmentation of forest covers however reduced the extent of their habitat, causing restricted movement of the Asian elephant (*Eliphus Maximus*) between adjacent habitats of 'Teknaf– Shilkhali– Whykheong– Inani– Ukhia– Ghundhum– Myanmar' and 'Dhoapalong– Himchari– Panerchara– Rajarkul– Naikhongchari' (Motaleb and Ahmed, 2016). As a result, thirty– eight elephants were trapped inside Cox's Bazar– Teknaf peninsula (National Geographic, 2018), often leading to human– elephant conflicts (UNHCR & IUCN Bangladesh, 2018). Evidence suggests that human– elephant conflict increased to a greater number in recent times that caused killing of 13 people since August 2017 (McVeigh and Peri, 2018; UNHCR & IUCN Bangladesh, 2018). Further, an increase of fuelwood consumption decreases fodder for elephant species, which is an utmost sign of deterioration of overall ecosystem health. Furthermore, unwise harvesting of forest biomass can jeopardize human wellbeing and ecological sustainability (Vogt et al. 2007 cited in Panja, 2020).

Based on population, physiography, accessibility and other factors (Table 3), this study predicted forest cover scenario for 2023 and 2027 (Fig. 4, Table 7) which revealed that, if current deforestation rate continues and no more Rohingya population is added further, the extent of degraded forest could increase to 3080 ha and 5120 ha, compare to 2019. This can enhance deterioration of ecosystem function and services in the study area, urgent actions are therefore warranted.

The findings of this work are generally aligned with observations across various settings of the world that the impact of refugees on the local environment can be staggering (Hagenlocher et al. 2012; Ndyeshumba, 2000), though primary outcome can be widespread deforestation (Black, 1994). Loss of natural resources is expected to continue in the coming years since repatriation is in halt despite many attempts of the host country, Bangladesh. Since the study area is very prone to landslide, further disappearance of forest cover would not only detrimental to environmental degradation but can lead to frequent slope failures, which may put both Rohingya and local communities at extreme risk of landslide hazards (Ahmed et al. 2020). As Rohingya populations (currently 932,940) in the study area outnumbered local population of 471,768 (BBS, 2011), various issues, besides environmental degradation, are often reported including social conflict between the two competing groups. We assert that the findings of this work can contribute significantly to devise strategies for conserving and managing forest ecosystem of an ecologically critical area. Hence, government of Bangladesh (GoB) and development partners can prioritize ecosystem management to promote ecological sustainability in the study area.

5. Conclusion

In the process of evaluating the impact of Rohingya influx to forest ecosystem function in Cox's Bazar– Teknaf peninsula, this study considered multiple factors to showcase present and future land use/cover change as well as loss of ecosystem function in an ecologically sensitive area. Multitemporal Sentinel imagery and collateral data were employed to quantify changes in forest cover and predict their distribution by incorporating important dynamic variables into the model. The results showed that forest cover degraded substantially to accommodate a large number of refugees that led to deterioration of forest ecosystem functions. Significant amount of above ground biomass loss and release of tons of carbons to the atmosphere in response to refugee rehabilitation were noteworthy. Importantly, this study quantified that 27,600 tons of carbon may have released to the atmosphere between 2017 and 2019 because of widespread deforestation. Further, modelling exercise indicated that the extent of forested lands and associated ecosystem functions could degrade substantially than might have anticipated at present. Consequently, wildlife habitat associated with forest degradation and fragmentation could endanger a number of flora and fauna, including the Asian elephant.

Despite this study has many implications (e.g. conservation of forest, policies), lack of cloud free satellite data was a major constraint to depict forest cover changes over different seasons. Hence, future work could use microwave data during the monsoon season and determine how regeneration of shrubs and mixed forest is occurring in the area. Taking regeneration of trees and shrubs into account may be useful to predict future changes of ecosystem functions. In addition, growth rate of Rohingya population was not considered in this study, accounting their growth rate could be of value to include in the dynamic model, used in this work. Finally, use of secondary data to estimate AGB may have under/over− estimated actual figures. Even though deriving biomass data from the field is time and labor− intensive, an ongoing work could provide better estimate related to biomass loss and carbon release, as a result of forest clearance, caused by Rohingya refugees. Despite these limitations, this work can be highly useful to determine the impact of refugee crisis on the environment with geospatial data in Bangladesh and elsewhere.

Conflict of Interest

The manuscript has been approved by all authors and has never been published, or under consideration at present for publication elsewhere. The authors confirm that there is no conflict of interest in publishing this research article by Land Degradation and Development journal.

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Table 1 Types of data used in this study

Data type	**Year**	**Spatial resolution**	**Source**
Sentinel 2A	2019–02–13 2018–02–18 2017–02–18	10 m	https://scihub.copernicus.eu/dhus/#/home
RapidEye	2015–2016	5 m	Bangladesh Forest Department (BFD)
World View–2	2011–2013	2 m	USAID
Google Earth images	2017–2019	<2 m	Google Earth Pro
Unmanned aerial vehicle (UAV) images	2017–2019	10 cm	United Nations High Commissioner for Refu
SRTM	2000	30 m	United States of Geological Survey (USGS)
National administration boundary	N/A	NA	Survey of Bangladesh (SOB)
Forest administration boundary	2015	NA	Bangladesh Forest Department (BFD)
Refugee camps	2019	NA	United Nations High Commissioner for Refu
Human trails	2017–2019	< 30 cm, <2 m	UAV image, Google Earth

Table 2 Land use and land cover classification scheme

LULC types	Descriptions
Agriculture (AC)	Perennial/seasonal agricultural activities
Saltpan (SP)	Salt production, drivers of forest degradation
Urban (UB)	Anthropogenic disturbances
Homestead vegetation (HS)	includes household vegetation and the houses underneath
Brick kiln (BK)	Anthropogenic stressors, drivers of degradation
Shrubs (SH)	Non-timber forest, low heights, grasses, and creeping vegetations
Mixed forest (MF)	Non-timber forest, mixed height forest with sparse tree canopies
Plantation forest (PT)	Young seedling and sapling, anthropogenic stimulus for forest health, reforestation
Canopy forest (CF)	Timber forest and healthy vegetation
Casuarina (CR)	Coastal vegetation with canopy coverage
Rohingya camps (CA)	A complete transformation of forest cover to other class
Degraded forest (DF)	Poor vegetation health
Creeks (CK)	small canals and streams
Waterbodies (WB)	Lake, ponds, rivers

Table 3 Suitable factors for forest degradation

Factors	Influencing LULC class(s)	Influence type	weight
Rohingya Population	Degraded forest	Stimulus	Very High
	Shrubs	Stressor	Very High
	Mixed forest	Stressor	Very High
	Canopy forest	Stressor	High
	Plantation forest	Stressor	High
	Rohingya camps	Stimulus	High
Distance from roads	Degraded forest	Stimulus	Medium
	Shrubs	Stressor	Medium
	Mixed forest	Stressor	Medium
	Canopy forest	Stressor	Medium
	Plantation forest	Stressor	Low
	Rohingya camps	Stimulus	High
Distance from human trails	Degraded forest	Stimulus	High
	Shrubs	Stressor	Low
	Mixed forest	Stressor	Medium
	Canopy forest	Stressor	Medium
	Plantation forest	Stressor	Low
	Rohingya camps	Stimulus	Medium
Distance from camp	Degraded forest	Stimulus	High
	Shrubs	Stressor	High
	Mixed forest	Stressor	High
	Canopy forest	Stressor	High
	Plantation forest	Stressor	High
Elevation	Degraded forest	Stressor	Medium
	Shrubs	Stimulus	High
	Mixed forest	Stimulus	High
	Canopy forest	Stimulus	High
	Plantation	Stimulus	Low
Distance from degraded forest	Degraded forest	Stimulus	High
	Shrubs	Stressor	High
	Mixed forest	Stressor	High
	Canopy forest	Stressor	High
	Plantation forest	Stressor	High

Table 4 Area statistics of LULC in the study area, 2017–2019

LULC types	2017		2018		2019	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Agriculture	9894.89	24.04	9627.35	23.39	9437.29	22.93
Saltpan	309.88	0.75	309.67	0.75	309.6	0.75
Urban area	49.62	0.12	41.39	0.10	41.41	0.10
Homestead vegetation	6013.54	14.61	5886.9	14.30	5804.79	14.10
Brick kilns	35.77	0.09	35.77	0.09	35.77	0.09
Shrubs	8801.55	21.38	8195.01	19.91	7306.34	17.75
Mixed forest	10593.09	25.73	9645.3	23.43	9303.84	22.60
Plantation forest	1210.04	2.94	1097.12	2.67	1049.58	2.55
Canopy forest	1463.85	3.56	1355.15	3.29	1278.99	3.11
Casurina	28.77	0.07	28.75	0.07	28.75	0.07
Rohingya camps	78.39	0.19	1261.95	3.07	1968.05	4.78

LULC types	2017		2018		2019	
Degraded forest	1862.69	4.53	2866.3	6.96	3792.02	9.21
Creeks	507.32	1.23	501.27	1.22	496.42	1.21
Waterbodies	312.99	0.76	310.46	0.75	309.54	0.75
Total	**41162.4**		**41162.4**		**41162.4**	

Table 5 Conversion of forest covers to refugee camps and degraded vegetation, 2017– 2019 (area in ha)

'From class'	'To class'	2017–2018	2018–2019
Agriculture	Camps	282.04	198.03
Homestead vegetation	Camps	130.42	85.35
Shrubs	Camps	302.41	54.17
	Degraded forest	398.59	851.17
Mixed forest	Camps	281.00	12.22
	Degraded forest	562.06	314.77
Planted trees	Camps	45.47	1.40
	Degraded forest	58.82	46.14
Canopy forest	Camps	76.18	3.98
	Degraded forest	40.13	72.09

Table 6 Correlation matrix, showing strengths of the relationship among six LULC categories and population

	Population	CF	MF	SH	PT	DF	CA
Population	1						
CF	-0.93669	1					
MF	-0.98126	0.986606	1				
SH	-0.84323	0.978074	0.931003	1			
PT	-0.97413	0.991593	0.999419	0.942903	1		
DF	0.906571	-0.99696	-0.9709	-0.99132	-0.9785	1	
CA	0.951057	-0.99905	-0.99278	-0.96807	-0.99629	0.992622	1

CF: canopy forest; MF: mixed forest; SH: shrubs; PT: plantation forest; DF: degraded forest; CA: camps

Table 7 Area statistics of predicted LULC for 2023 and 2027

LULC types	2023	2027	Area change (2019–2023)	Area change (2019–2027)
Agriculture	9450.82	9465.92	13.53	-28.63
Saltpan	309.5	309.44	- 0.1	-0.16
Urban	41.41	41.41	0.0	0.0
Homestead vegetation	5804.41	5803.26	-0.38	-1.53
Brick kiln	35.77	35.77	0.0	0.0
Shrubs	5800.1	4871.53	-1506.24	-2434.81
Mixed forest	8039.04	7144.4	-1264.8	-2159.4
Planted young forest	911.48	816.62	-138.1	-232.96
Canopy forest	1109.63	990.62	-169.36	-288.37
Casurina patches	28.75	28.75	0.0	0.0
Rohingya camps	1968.98	1972.05	0.93	4.0

LULC types	2023	2027	Area change (2019–2023)	Area change (2019–2027)
Degraded forest	6872.12	8911.04	3080.1	5119.02
Creeks and streams	482.24	464.85	-14.18	-31.57
Waterbodies	308.14	306.73	-1.4	-2.81

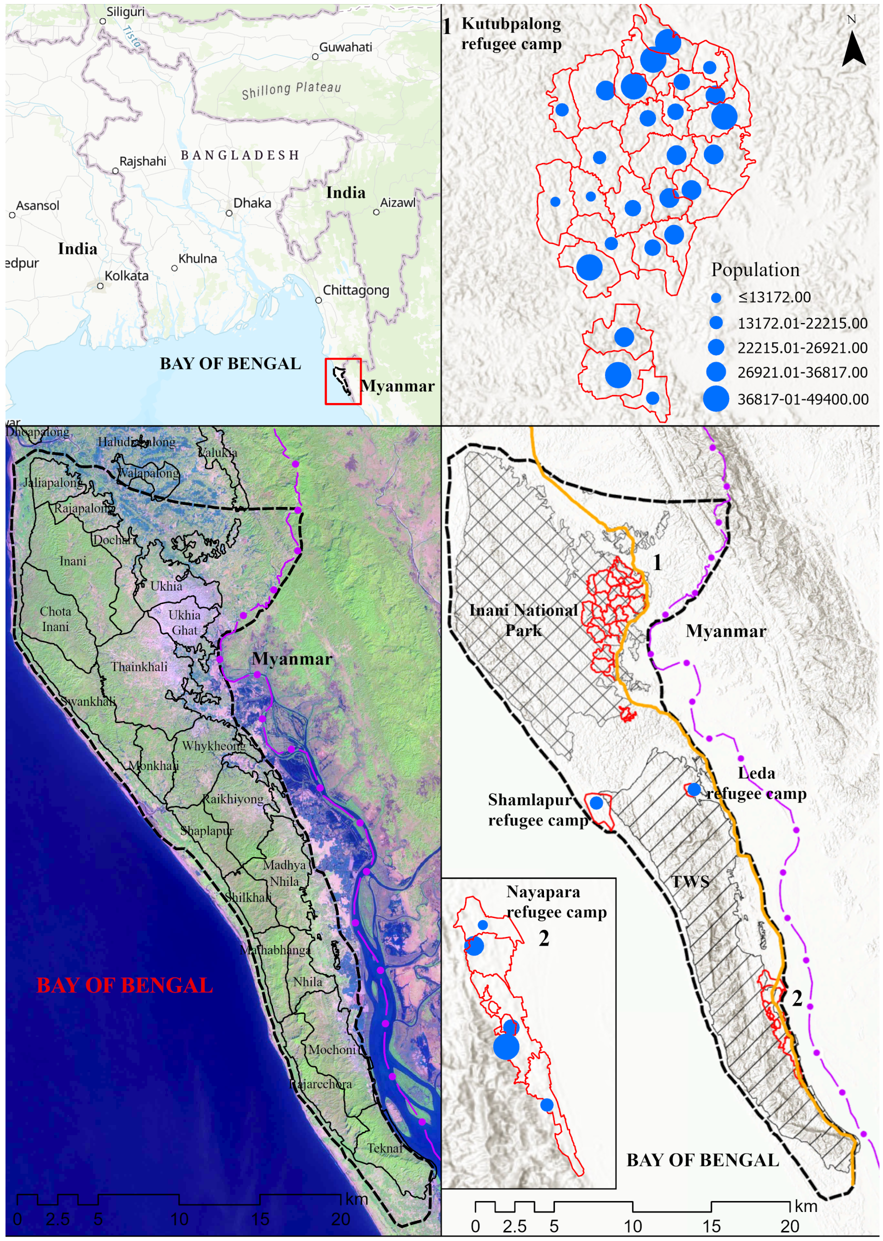
Area in ha, '-' denotes loss and '+' represents increase

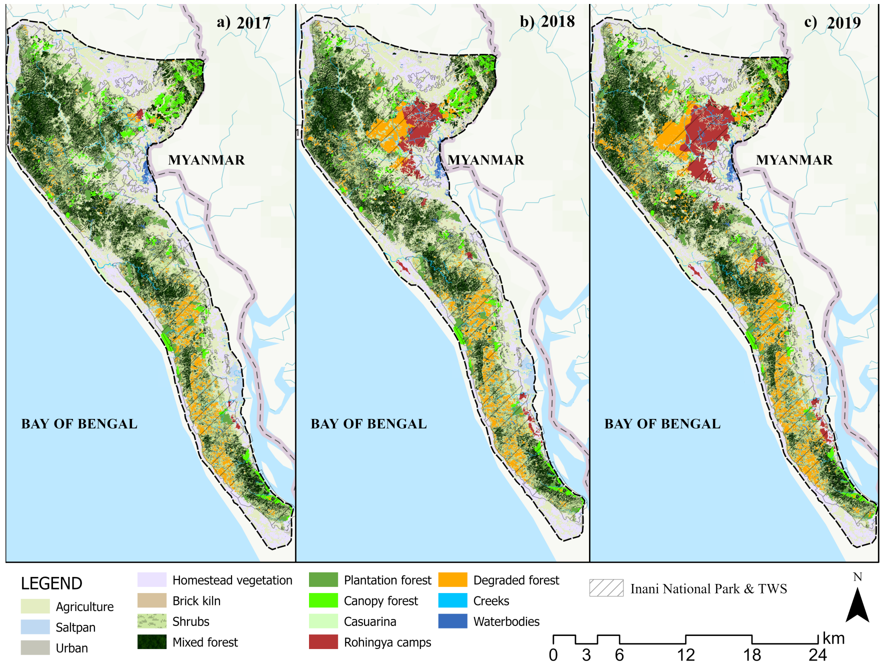
Table 8 Predicted degradation of major forest covers in 2023 and 2027 (area in ha)

LULC types	2023	2023	2027	2027
	Camps	Degraded forest	Camps	Degraded forest
Agriculture	–	–	–	
Homestead vegetation	–	–	–	
Shrubs	–	1585.39	–	2538.17
Mixed forest	–	1185.65	–	2056.08
Planted trees	–	127.7	–	218.02
Canopy forest	–	179.76	–	303.31

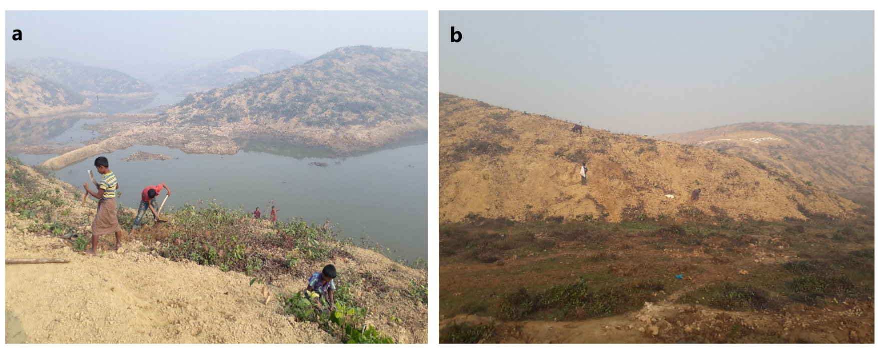
Table 9 Changes in biomass and carbon stocks in Cox's Bazar– Teknaf peninsula, 2017– 2027

Forest types	Existing and projected loss of biomass and carbon (ton)	Existing and projected loss of biomass and ca
	2017	2017
	AGB	Carbon
Shrubs	18	9
Mixed forest	180114	90057
Plantation forest	2	1
Canopy forest	263549	131774
Total	**443683**	**221841**

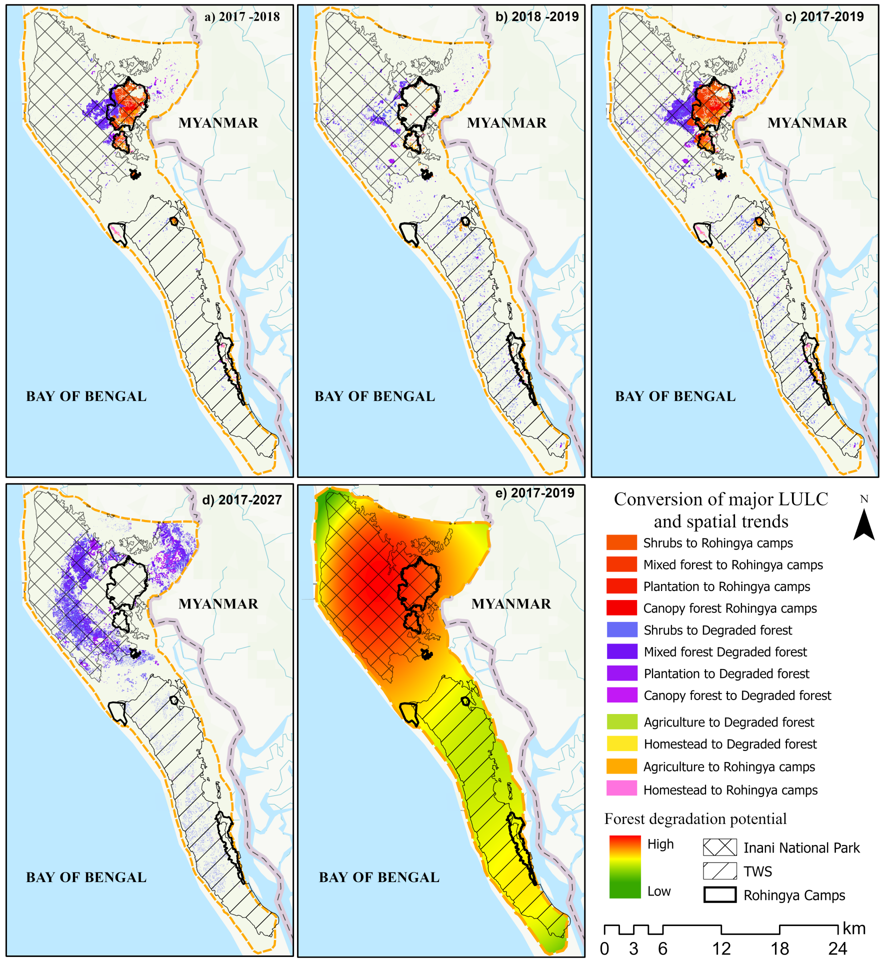

Siliguri
Tista
Guwahati
Shillong Plateau
BANGLADESH
Rajshahi
India
Asansol
Dhaka
Aizawl
India
Khulna
Kolkata
Chittagong
BAY OF BENGAL
Myanmar
1 Kutubpalong refugee camp
N
Population
≤13172.00
13172.01-22215.00
22215.01-26921.00
26921.01-36817.00
36817-01-49400.00
Jaliapalong
Rajapalong
Haludiapalong
Palong
Ukhia
Inani
Chota Inani
Ukhia Ghat
Thainkhali
Myanmar
Whykheong
Raikhiyong
Shaplapur
Madhya Nhila
Nhila
Mochoni
Teknaf
BAY OF BENGAL
0 2.5 5 10 15 20 km
1
Inani National Park
Myanmar
Leda refugee camp
Shamlapur refugee camp
TWS
Nayapara refugee camp
2
2
BAY OF BENGAL
0 2.5 5 10 15 20 km

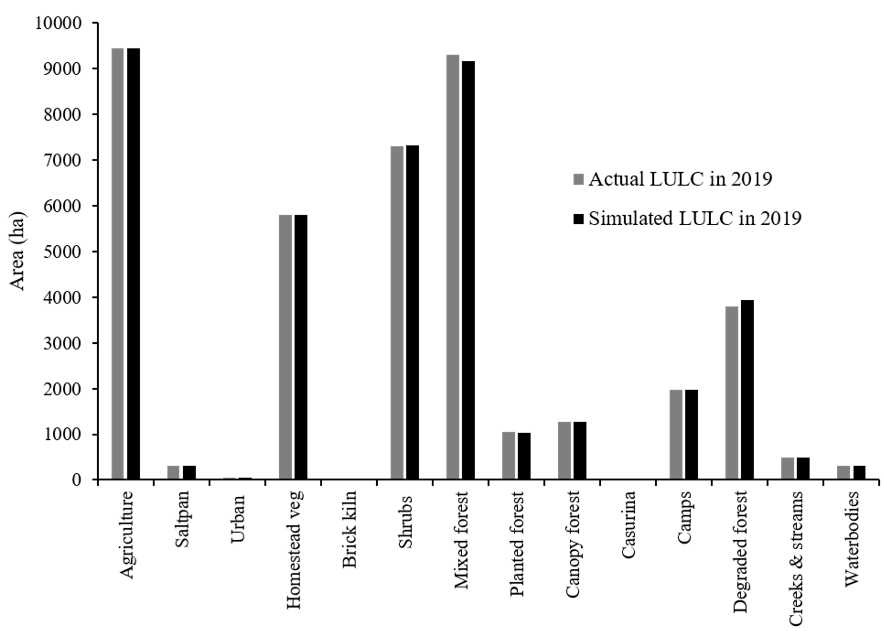


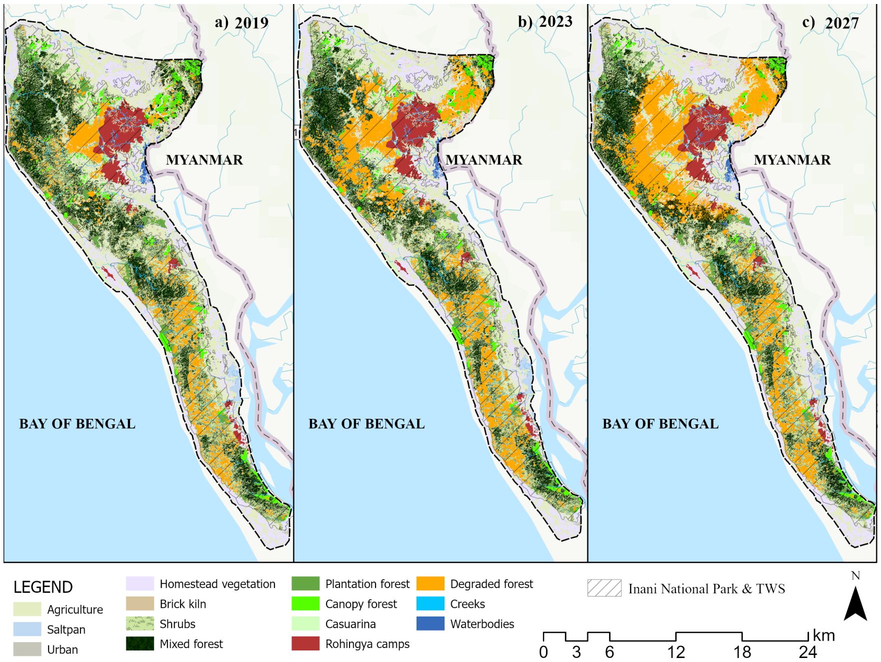
a) 2017
b) 2018
c) 2019
MYANMAR
BAY OF BENGAL
LEGEND
Agriculture
Saltpan
Urban
Homestead vegetation
Brick kiln
Shrubs
Mixed forest
Plantation forest
Canopy forest
Casuarina
Rohingya camps
Degraded forest
Creeks
Waterbodies
Inani National Park & TWS
N
0 3 6 12 18 24 km

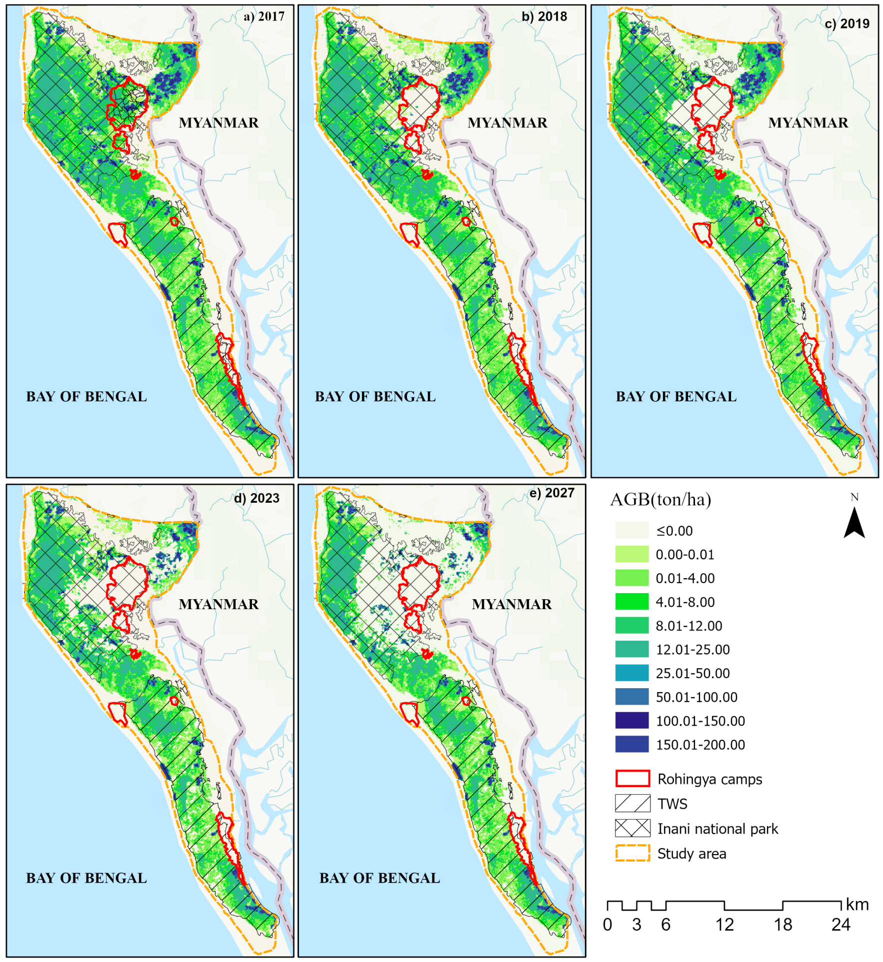


a
b


a) 2017 -2018
b) 2018 -2019
c) 2017-2019
d) 2017-2027
e) 2017-2019
MYANMAR
BAY OF BENGAL
Conversion of major LULC and spatial trends
N
Shrubs to Rohingya camps
Mixed forest to Rohingya camps
Plantation to Rohingya camps
Canopy forest Rohingya camps
Shrubs to Degraded forest
Mixed forest Degraded forest
Plantation to Degraded forest
Canopy forest to Degraded forest
Agriculture to Degraded forest
Homestead to Degraded forest
Agriculture to Rohingya camps
Homestead to Rohingya camps
Forest degradation potential
High
Low
Inani National Park
TWS
Rohingya Camps
0 3 6 12 18 24 km


Area (ha)
10000
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
Actual LULC in 2019
Simulated LULC in 2019
Agriculture
Saltpan
Urban
Homestead veg
Brick kiln
Shrubs
Mixed forest
Planted forest
Canopy forest
Casurina
Camps
Degraded forest
Creeks & streams
Waterbodies


a) 2019
b) 2023
c) 2027
MYANMAR
BAY OF BENGAL
LEGEND
Agriculture
Saltpan
Urban
Homestead vegetation
Brick kiln
Shrubs
Mixed forest
Plantation forest
Canopy forest
Casuarina
Rohingya camps
Degraded forest
Creeks
Waterbodies
Inani National Park & TWS
N
0 3 6 12 18 24 km


a) 2017
b) 2018
c) 2019
d) 2023
e) 2027
MYANMAR
BAY OF BENGAL
AGB(ton/ha)
≤0.00
0.00-0.01
0.01-4.00
4.01-8.00
8.01-12.00
12.01-25.00
25.01-50.00
50.01-100.00
100.01-150.00
150.01-200.00
Rohingya camps
TWS
Inani national park
Study area
N
0 3 6 12 18 24 km