Understanding the political ecology of forced migration and deforestation through a multi-algorithm classification approach: the case of Rohingya displacement in the southeastern border region of Bangladesh

Nahian Ahmed (a), M. Naimul Islam (a), M. Ferdous Hasan (a), Tamanna Motahar (a) and Mohammad Sujauddin (a) (b)

(a) Department of Electrical and Computer Engineering, School of Engineering and Physical Sciences, North South University, Dhaka, Bangladesh; (b) Department of Environmental Science and Management, School of Health and Life Sciences, North South University, Dhaka, Bangladesh

ABSTRACT

Compared with numerous existing forced migration scenarios across the globe, migration from Myanmar to Bangladesh through southeastern border region is unique at least for three reasons – (i) very large number of migrants have been displaced to (ii) a very small area in (iii) a relatively short period of time, creating an obvious cumulative impact on forest cover area of the host country. Therefore, this study aims to analyze the dynamics of refugee migration and deforestation in Bangladesh. Satellite images of Landsat-5 & 8 and Sentinel-2 were classified via four different classification algorithms (SVM, Random Forest, CART, and Max Entropy) to measure major land use and land cover changes, namely, (i) dense forest, (ii) sparse forest, (iii) open area, and (iv) settlement from 1988 to 2018. The analysis revealed a declining trend of dense forest area, majority of which took place from 2016 to 2018 triggered by Rohingya migration. As a whole, the dense forest cover has been effectively halved (8531 ha in 2016 to 4498 ha in 2018) in the span of just two years while refugee settlement has increased nine-folds (271 ha in 2016 to 2679 ha in 2018). Aggregated and indisputable conclusion has been derived indicating that forced Rohingya migration and deforestation are indeed positively correlated.

1. Introduction

Forced migration is a global phenomenon that has been widely perceived by the international community due to its effects on social transformation and its political significance (Castles, 2003). The United Nations High Commission for Refugees has given recognition to migration issues in regions such as Central African Republic, South Sudan, Iraq, Syria, Ukraine, Myanmar-Bangladesh, etc. (Batterbury, 2001; Hammer, 2004; Kalipeni & Oppong, 1998; Noss, 1997; UNHCR, 2018). As a result, the political ecology of these regions has been receiving much attention in recent times. Mass population movement in the form of migration can have several obvious consequences. Migration and environmental impact are interrelated to the extent that the relationship between these forces appears to be mutually inclusive in most cases. Numerous extant literature have prevailed in depicting, analyzing, and summarizing the environmental causes of migration and the issues of environmental migrants (Black et al., 2011; Homer-Dixon, 1991; Molvaer, 1991; Myers, 2002; Westing, 1991). However, emphasis on environmental impacts of migration is of utmost importance (Black, 1994; Kibreab, 1997; Oucho, 2007), considering that the state of the environment in turn affects migration and migrants. Unfortunately, even after the extensive assessment of the environmental impacts of forced migration, due attention has not been received so far.

One of the silent but direct consequences of this discourse is deforestation. This particularly holds true for host regions containing forested areas. For example, population growth owing to forced migration has been reported to be a key contributor to deforestation in Indonesia (Darmawan, Klasen, & Nuryartono, 2016). Thus, migration can be posited as the driving force behind accelerated deforestation (Grimm & Klasen, 2015; Klasen, Faust, Grimm, & Schwarze, 2010). Competition for land between locals and migrants is inevitable if land is scarce, leading migrants to resort to forested lands for use. When compared to locals, migrants tend to have relatively more negative consequences on the forests of the host region (Codjoe & Bilsborrow, 2011).

Taking into account the aforementioned regions where forced migration took place in recent years, Rohingya migration is one of the most prominent and urgent cases in terms of its previous influx as well as its recent explosion (for details, see Section 2). From the huge family of Indo-Aryan/Indic languages...
of Southeast Asia consisting of hundreds of languages such as Bengali, Gujarati, Marathi, Punjabi, etc., the Rohingya language is spoken by approximately 1.1 million people (Solomon, 2017). The synonymous use of the same word to denote both a language and the people who practice it, combined with recent turn of sociopolitical events, has led to the use of the term Rohingya in a derogatory sense. Historical difference in nationalistic views may exist within a population, based on conflict between defining a country according to its geopolitical international boundaries compared to defining a country according to the corresponding ethnic divisions existing among the population, which has led to the Myanmar government stigmatizing the Muslim population residing within Rakhine (Arakan) state (Cheung, 2011).

Continents of South America, Africa, and Asia comprise majority of the world’s tropical rainforests, among which Asia has been subjected to the highest deforestation rates (Hansen et al., 2008). Bangladesh is not an exception to the Asian deforestation trend. The total forest area of the country has shrunk from 2,314,000 ha in 1930 to 1,408,600 in 2014 (net loss of 905,400 ha) (Reddy, Pasha, Jha, Diwakar, & Dadhwal, 2016). Forest Management Wing of Forest Department of Bangladesh has classified the entire country into five different circles, namely, coastal (southern coast), central (center and northeastern region), Chittagong (southeastern region), Rangamati (hilly area of southeastern region), and Khulna (southwestern region) (Forest Department, 2018). According to Choudhury and Hossain (2011), the Cox’s Bazar forest division consisted of 30,398 ha of natural forests and 19,084 ha of plantation forests. The southeastern border region which falls within Cox’s Bazar division has been affected by migration from Myanmar for several decades since the Myanmar government declared laws that excluded the Rohingya ethnicity as legal citizens in 1982 (Cheung, 2011). However, over the last year (2017–2018), the region has seen explosive refugee population growth (population details on migration from Myanmar to Bangladesh through the southeastern border region have been provided in the following sections).

The existing literature pool suggests that social and environmental impact due to migration received large attention across the globe, focusing on environmental health and sanitation (Hankins, Friedman, Zafar, & Strathdee, 2002; Noji, 2005; Toole & Waldman, 1997), the context of pollution (Hugo, 1996; Hunter, 2005; Lucas, Wheeler, & Hettige, 1992), socioeconomic vulnerabilities (Chaaban et al., 2010; Cheung, 2011; O’Mahoney and Donnelly, 2010; Poncelet et al., 2010), etc. However, study on deforestation due to migration is scanty even though it demands equal, if not more attention, in comparison to aforementioned consequences of migration with few exceptions (Darmawan et al., 2016; Fraser, 1998).

Compared with numerous existing forced migration scenarios across the globe, migration from Myanmar to Bangladesh through southeastern border region is unique at least for three reasons – (i) very large number of migrants have been displaced to (ii) a very small area in (iii) a relatively short period of time, creating an obvious cumulative impact on forest cover area of the host country, thus warranting sufficient attention towards the aspect of deforestation. Hence, this study, first of its kind, aimed at providing historical overview (spanning 30 years) of land use change (forest cover vs refugee settlement) across the southeastern border region of Bangladesh due to migration from Myanmar, as well as the magnitude of impact of migration via multi-satellite and multi-algorithm approach.

2. Materials and methods

2.1. Overview of study area

2.1.1. Study area

The study sites lie within the southeastern border region of Bangladesh, neighboring the Bangladesh—Myanmar international boundary, placing the areas in close proximity to refugee movement corridors. The study area is divided into two regions (Figure 1), namely, (i) the northern study area and (ii) the southern study area. The northern study area is situated in Cox’s Bazar district (comprising Balukhali Bazar and Waikhyang of Palong Khali union (smallest rural administration), Ukhaa upazila (sub-district)). However, refugee camps of the northern study area have spread to Bandarban district (one of the three hill districts of Bangladesh) Naikhyonchari upazila (Ghandung union’s Gundum Bazar area) and thus being a small part of the northern study area as well. The southern study area also falls within Cox’s Bazar district comprising Teknaf upazila’s1 Nihua union, covering Atikhalipara, Dhundumia, and Jadipara. The total study area covers 16,428 ha including the most populated 25 camps. The northern study area (falling in Cox’s Bazar and Bandarban district, Figure 1) covers 15,103 ha and southern area (falling within Teknaf peninsula of Cox’s Bazar district, Figure 1) covers 1325 ha. Noteworthy is that the northern study area covers approximately 92% of the total study area.

2.1.2. Study area selection

The study area was narrowed down based on Rohingya camp location datasets (ISCG, 2018). Finding the land use change directly due to migration

---

1“Teknaf Peninsula is one of the longest sandy beach ecosystems (80 km) in the world” (Chowdhury, Hoffsin, Mitra, & Barua, 2011).
was given the utmost importance. It is necessary to ensure that required steps were taken during the study area selection process to minimize the effect of land use change due to nonmigrant anthropogenic factors. Constrained spatial resolution of satellite images limits the effectiveness of photointerpretation. The study area selection process follows several steps and has been summarized in Figure 2.

2.1.2.1. Population growth of Rohingya migrants. The total population of Rohingya refugees living in Cox’s Bazar is estimated 212,518 before August 25 in 2017, which is almost 24.5% of the current population of 883,785 (ISCG, 2018). Refugee population growth is shown in Figure 3. From August 2017 to September 2017, the population grew at a staggering rate of almost 191%. The first decline in population growth happened in February 2018.

2.1.2.2. Settlement type distribution compared to settlement type population distribution. According to the dataset of ISCG (2018), as of 25 February 2018, there are 119 camps in total with 25 of them harboring zero population. The camps are of five types – the border points are the corridors via which refugees entered into Bangladesh, refugee camps are planned areas specifically built for migrants, spontaneous sites refer to totally unplanned camp sites, makeshift
settlements have temporary and vulnerable shelters for refugees, and the host communities include the areas provided by the local population. Figure 4(a) shows the settlement type distribution of the 119 camps and it suggests that the major number of camps are host communities (68.9%).

Figure 2. Flowchart of study area selection process.

Figure 3. Migrant population growth (extracted from ISCG, 2018).
The total population is distributed among 94 camps. Figure 4(b) shows the population distribution among the five types of camps. As it shows, the major population resides in spontaneous site camps although the number of camps is only 25. The total population in spontaneous sites on 25 February 2018 is 725,827, approximately 82% of the total recorded population.

2.1.2.3. Assessing number of camps containing majority of the population. Figure 5 is a representation of population growth among the camps sorted by population. As the figure suggests, most of the population resides in 30 camps among 119 camps. However, 23 of the 30 camps are of spontaneous sites, 4 are host communities, 2 refugee camps and 1 makeshift settlement. Furthermore, the 3 host communities and 2 spontaneous sites of the 30 camps in question remain undetectable due to the spatial resolution of satellite images. Thus, the study emphasized on the 25 remaining camps.

2.1.2.4. Site selection process. The area selection process involves finding a balance between inclusion of areas directly impacted primarily due to migration and noninclusion of areas not directly affected or having negligible effects of migration. The sand of the coastline and urban areas such as towns and cities showed very similar spectral signature compared to refugee settlements. Therefore, to minimize the effect of unwanted factors which may lead to overestimation of settlement area if not preprocessed, the coastline and preexistent urban areas were not included in the study area.

As a result, the northern study area contains 22 of the most populated 25 camps. These 25 camps under the study have a population of approximately 765,975 which is 86.6% of the total population. The northern study area has a population of 703,881, approximately 92% of the population among 25 camps and 79.6% of the total population. The historical change in land use of the region subjected to recent Rohingya migration has been analyzed and discussed in the following sections.
2.1.3. Time period
The time period of the study spans 30 years, starting from 1988 till 2018. Knowledge about historical change in land use of the region is essential to estimate deforestation directly due to migrant displacement. A major part, over 600,000, of the Rohingya population entered Bangladesh after 25 August 2017. Thus, it is paramount to make sure that the land use from 2017 is directly compared to land use in 2018.

2.1.4. Data collection
The dataset (ISCG, 2018) contains information such as camp name, settlement type, district, upazila, union, population, latitude, longitude, etc. The datasets contain information about the camps from August 2017 till February 2018. The latest dataset collected is from 25 February 2018, which was used for the rigorous process of study area selection.

Satellite image sources include Landsat-8, Landsat-5, and Sentinel-2. Landsat images are from Tier 1 of Collection 1, regarded as the most fitting for time series analysis preprocessed to orthorectified TOA (top of atmosphere) reflectance (Chander, Huang, Yang, Homer, & Larson, 2009). Details of collected satellite image data are summarized in Table 1.

2.2. Method
2.2.1. Classification
2.2.1.1. Classes. Assigning classes depend on the study area and purpose of the study (Churches, Wampler, Sun, & Smith, 2014; Torahi and Rai; 2011; Weng, 2002). Photointerpretation of images shows several basic trends. Forest cover can be visually separated into two classes, with the first class of dense forest consisting of areas where non-fragmented forest areas are visible. The second class, sparse forest, has fragmented forests giving it a comparatively faded shade compared to dense forest areas. Cultivated and uncultivated lands were both designated in the same class of open area class. The fourth class is refugee settlement area, as camp area estimation is integral part of the study. Thus, the images were classified into four classes, namely, dense forest, sparse forest, open area, and settlement.

2.2.1.2. Classification algorithms. Unsupervised learning/classification techniques tend to have low accuracy (Love, 2002). Owing to this, we have opted to go for supervised classification approach. Four supervised classification algorithms have been used, namely, Support Vector Machine (SVM) (Cortes & Vapnik, 1995), Random Forest (Breiman, 2001), Max Entropy (Mcdonald, Mohri, Silberman, Walker, & Mann, 2009), and Classification and Regression Trees (CART) (Breiman, Friedman, Olshen, & Stone, 1984). All algorithms, except Max Entropy, have been widely used in satellite image classification (Immitzer, Atzberger, & Koukal, 2012; Thanh Noi and Kappas, 2017). The same training data was provided to all four algorithms to maintain consistency.

2.2.1.3. SVM. SVM is a state-of-art classifier mostly used in pattern recognition and bioinformatics (Chu, Jin, & Wang, 2005). This classifier works on kernel method which acquires data through dotproducts. The advantage of the kernel function is that a linearly designed classifier can predict nonlinear decisions. The kernel function can also forecast if the data area is not fixed with vector representation. Usually, SVM is a linear two-class classifier.

If \( x \) is a vector with \( x_i \) component where \( x_i \) is the \( i \)th vector in a dataset and a specific pattern, for the linear classifier, an inner product or scalar product \( w^T x \) is calculated where \( w^T x = \sum w_i x_i \), here \( w \) is a weight vector and \( T \) means transpose vector. The linear discriminant function for the classifier is \( f(x) = w^T x + b \) (\( b \) denotes bias). Considering \( b = 0 \), if the \( x \) points are such that \( w^T x = 0 \), all the resulting points will be perpendicular to \( w \) and will go across the origin. Moreover, if the plane is in three dimensions, the resulting two-dimension line will be a hyperplane which will divide the total plane into two regions and the bias \( b \) will push the plane away from the origin. The equation of the hyperplane is \( \{ x : f(x) = w^T x + b = 0 \} \).

The sides of the divided regions are determined by the sign of the discriminant function \( f(x) \) and the boundary between the regions is called the decision boundary of the classifier. If the decision boundary depends on linear data, it is called linear classifier,
and if data is nonlinear, the classifier is defined as nonlinear classifier.

2.2.1.4. Random Forest. Random Forest is a classifier for supervised learning which employs the collection of tree predictors where the independently sampled random vector values determine each tree construction (Breiman, 2001). Here, individual tree decisions are combined. If the forest is sufficiently deep, it produces more precise prediction. The Random Forest algorithm works according to the following:

For each tree $b$ from total $B$ number of trees,

(a) Select any random data $Z$ from $N$ number of training data
(b) Create the random forest tree $T_b$ by continuing the following steps on each leaf of the tree until the minimum node size $n_{min}$ is achieved.
   i. Randomly select $m$ variables from $p$ variables
   ii. Select the best split point from $m$
   iii. Split the node into two children nodes according to the split point
(c) Combine the outputs of all trees as $\sum_{b=1}^{B} T_b(x)$

For the new prediction any point $x$, the regression will be

$$F^b(x) = \frac{1}{B} \sum_{b=1}^{B} T_b(x)$$

2.2.1.5. CART. CART is a combination of classification and regression tree used for supervised learning (Morgan, 2014). While to predict the outcome of numeric or continuous data variable, a regression tree is deployed. And depending on the homogeneity, data classification is done by classification tree after filtering the noise. In CART approach, the dataset is partitioned into smaller subsections recursively until the smaller cells are grouped together with same label with the maximum “accuracy”. The “pruning” value validates the accuracy of the prediction. If there are $X$ number of numeric or continuous dataset of $I$ labels, there are $2^{I-1} - 1$ possible partitions of predictors. So, the CART algorithm goes as follows:

(a) Find each predictor’s best subset point by examining all possible subsets, for a node $N$, the best subset $S$ is determined to maximize the split condition $\Delta t(S,N)$.
(b) Find the data node’s best partition. Among the best subset from step a which maximizes the splitting criteria, is used to do the partition.
(c) Continue splitting the remaining data nodes until the stop condition matches.

2.2.1.6. Max Entropy. Maximum Entropy classifier (Mcdonald et al., 2009) operates based on maximum entropy principle and selects the data with maximum entropy from all training data. If the prior distribution and conditional dependency are unknown and it is difficult to assume any prediction, this classifier is deployed. Usually, this classifier is used to classify contextual information like characters within a text.

If $m$ is the number of words in a document ($w_1, w_2, \ldots, w_m$), there is a binary valued sparse array which defines if a particular word $w_k$ is present in the document or not. The empirical probability distribution for this scenario is defined by

$$\hat{p}(x, y) = \frac{1}{N} \times \text{number of times}(x,y) \text{ occurs in the document}$$

In the statistical model of this random process, if $x$ is the information residing in the $y$ class, an indicator function $f(x,y)$ is described to find in a document, if $y$ belongs to a class $c_i$ and the document contains the word $w_k$. The indicator function will output binary value (0 or 1) as the “feature” of that document (Pang, Lee, & Vaithyanathan, 2002).

$$f_i(x,y) = \begin{cases} 1 & \text{if } y = c_i \text{ and } x \text{ contains } w_k \\ 0 & \text{otherwise} \end{cases}$$

The binary result of the feature is incorporated to calculate the new empirical distribution as

$$\hat{p}(f_i) = \sum_{x,y} \hat{p}(x,y)f_i(x,y),$$

which usually results in $1/N$ if each training sample $(x,y)$ happens once in the training dataset. The expected value of the feature according to the model $p(y \mid x)$ is

$$\tilde{p}(f_i) = \sum_{x,y} \hat{p}(x)p(y \mid x)f_i(x,y)$$

To make the expected data equal to the experimental data, the two equations are compared as follows:

$$\sum_{x,y} \hat{p}(x)p(y \mid x)f_i(x,y) = \sum_{x,y} \tilde{p}(x,y)f_i(x,y)$$

This is called “constrain” that can be demonstrated for infinite number of models. To get the maximum entropy, the optimum model of training set is to be chosen.

2.2.1.7. Area calculation. The areas were calculated by finding the number of pixels that fall within each class of a classified image. The number of pixels of each class is multiplied by the area of each pixel to obtain area is square meters, which is then converted to hectares.
2.2.1.8. Software uses. The maps were created using ArcGIS software. The visualizations were generated using numpy, pandas, and matplotlib packages of Python 3. All geoprocessing, classification and area calculation were achieved via the JavaScript API of Google Earth Engine (Gorelick, Hancher, Dixon, Ilyushchenko, Thau, & Moore 2017). Google Earth Engine provides over 15 classification and clustering algorithms and removes the step of downloading memory intensive satellite images, since all geoprocessing occurs on Earth Engine servers and not on the user/client’s machine. Parallel processing provides much faster computations as well as computations not possible on the client’s machine.

3. Results and discussion

3.1. Land use change from 1988 to 2018 in southeastern border region of Bangladesh

3.1.1. Image classification and algorithm comparison
The image classification and algorithm comparison of the study area are summarized in this section. For image classification, land use change from 1988 to 2018 was analyzed using Landsat-5 & 8 satellite images via four algorithms (SVM, Random Forest, Max Entropy, CART) (Figure 6), while for algorithm comparison, each classification algorithm was compared based on four land uses (Figure 7).

Image analysis suggested that the classified images of 1988 show a large percentage of the study area had dense forests (approximately 54% and 52% according to CART and Random Forest classifiers, respectively). All classification algorithms confirmed an abrupt declining trend (approximately halved) of dense forests during the initial time period of the study (1988–1998), further exacted by the inclining trend of sparse forests implying deforestation through the conversion of dense forests to sparse forests. However, output of classification algorithms shows variability. For example, from 1988 to 1998, open area showed an inclining trend according to SVM and Max Entropy classifiers and a declining trend according to Random Forest and CART classifiers.

Further investigation of study area after 10 years (1998–2008) revealed that dense forests area increased, sparse forest area decreased, while open area showed an increasing trend compared to 1998 classification results. This finding is in conformity with Bangladesh Forest Department’s endeavor of 19,084 ha plantation forest in Cox’s Bazar area recorded in 1996 (Choudhury & Hossain, 2011). Even though migrant population existed in Bangladesh in 2008 (IRIN, 2008), camps were virtually undetectable.

Images of 2018 compared to 2008 showed sharp decrease of dense forest (confirmed by all algorithms). It is to be noted that the year 2018 has the lowest dense forest area in the last 30 years of the region’s history, implying massive deforestation which may be due to Rohingya migration from Myanmar to Bangladesh conformed to ISCG (2018). Furthermore, simple visual superimposition is sufficient to infer that refugee camps have replaced dense forest area (confirmed by consistency of all algorithms). However, variations in output of classification algorithms were observed for sparse forest

Figure 6. Land use change from 1988 to 2018 in the northern study area using Landsat 5 and 8 satellite images via four algorithms (SVM, Random Forest, Max Entropy, CART).
Overall, satellite image analysis for all land uses from 1988 to 2018 revealed that Random Forest and CART classifiers are more or less consistent with each other, while Max Entropy and SVM classifiers exhibited non-coherence in some cases. Both CART and Random Forest algorithms are based on decision tree models, explaining the similarity of results achieved by the two algorithms. Photointerpretation of resultant classified images show that hierarchy-based decision boundaries are more accurate than hyperplane decision boundary of SVM and entropy-based decision boundary of GMO Max Entropy. Owing to this, for further analysis, we have opted to utilize Random Forest and CART to investigate the impact of Rohingya migration during 2016–2018 using Landsat-8 and Sentinel-2 satellite images which has been discussed in the following section.

### 3.2. Impact of migration on land use change from 2016 to 2018

#### 3.2.1 Impact of Rohingya migration on land use

As mentioned above, Rohingya migration rate was negligible before 25 August 2017. Since then, explosive forced migration from Myanmar to Bangladesh through southeastern border region was reported (ISCG, 2018). To concretely conceptualize the impact of Rohingya migration on deforestation, both Landsat-8 and Sentinel-2 images were analyzed. Land use change due to Rohingya migration from 2016 to 2018 has been summarized in Figure 8. The classified satellite images show that all classification schemes (Landsat-8 images classified via Random Forest, Landsat-8 images classified via CART, Sentinel-2 images classified via Random Forest and Sentinel-2 images classified via CART) are very consistent to each other even though there is use of different algorithms (CART and Random Forest) and different satellites with different spatial resolutions (Landsat-8 and Sentinel-2).

Southeastern border region of Bangladesh has been an environmental victim of Rohingya migration in the context of massive deforestation. Concrete numerical values and derived trends are portrayed in Figure 9. Culmination of analysis derived from two different satellites and two different classification algorithms provides indisputable proof of correlation between deforestation in the region and Rohingya migration.

#### 3.2.2 Impact of migration on deforestation

Mass migration of Rohingya population occurred in the year 2017 (ISCG, 2018). The average values of calculated areas using Landsat-8 images classified via Random Forest, Landsat-8 images classified via CART, Sentinel-2 images classified via Random Forest and Sentinel-2 images classified via CART, and derived statistics are portrayed in Table 2 which
emphasizes on the stark differences in land cover of dense forest and refugee settlement that has happened between 2016 (before mass migration) and 2018. The dense forest cover area of the southeastern border region has been effectively halved in the span of just two years while refugee settlement area has increased nine-folds. Both Figure 8 and Table 2 imply that as refugee settlement area increases, dense forest area decreases, suggesting the fact that migration and deforestation are indeed correlated.

4. New nexus and the way forward

Forced migration scenarios across the globe on a large scale are rare but important due to historical...
significance. However, study on dynamics of forced migration and deforestation is scarce. We have tried to overcome this issue via specialized region-based approach in order to address the unique aspects of the host region which might open a new window into the future directions based on this work, some aspects of which have been discussed along with our specialized approaches.

Collection of data (and eventually knowledge) of refugee situations can be performed via two primary methods, namely, manual ground data collection and remote sensing of the region. Manual data collection can be slow and prone to limitations of accessibility of physical locations. However, remote-sensing techniques provide a fast and efficient method to monitor refugee situation dynamics. Forced migration scenarios can be subject to rapid spatial and temporal changes, indicating the suitability of use of remote sensing. When it comes to land use and land cover change analysis, the task of assigning land use classes and applying appropriate classification techniques is important. However, analysis of land use and land cover change of events such as forced migration requires a more specialized approach of study area selection. The importance of this step influences both land use class assignment and classification techniques. Forced migration are historical events triggered and triggering the complex dynamics of politics, economics, environment, and legislation on an international scale. Thus, it is of the utmost importance to not select arbitrary study areas, which in turn affects following steps of land use assignment and classification, the results of which in turn shape the global views towards the host region and refugees. Rather, an equilibrium was achieved during the study area selection process in order to find the right balance between avoiding incorrect overestimation of negative impacts of migration which portrays refugees as environmental degraders of the host region, and avoiding underestimation which obscures the true state of the negative impacts of migration. To address the error minimization, we have duly considered the aforementioned features.

The efficiency of the task of conservation and regeneration of forests of the southeastern border region is influenced by knowledge on the most vulnerable areas. Steps undertaken by administrative institutions such as the Forest Department play an immense role in forest conservation. The data and summary derived from the study can directly be an aid in the task of efficient delivery of resources for forest conservation and regeneration. The process of deforestation is specially disastrous to a host region due to the fact that the process releases captured carbon back into the atmosphere, raising carbon dioxide levels as well as reducing the carbon sequestration ability of the affected areas of the host region. Spatial and physical dimension distributions of various tree species of the southeastern border region of the country present in existing literature combined with the forest loss areas derived in the study can be used to estimate the carbon stock depletion levels as well as environmental-economic losses of forced migration. Overview of refugee situations obtained via remote sensing methods and further analysis are not only useful for approximating impact of migration on land use and land cover change. Strategic decisions undertaken by administrative institutions based on background knowledge on land cover of the host region during camp site planning and allocation can greatly reduce the destructive effects on the forests. Finding the right balance between the lowest possible environmental impact and greatest possible logistical accessibility can lead to the optimum camp sites, which requires previous knowledge on land use and land cover change of the region. Other factors such as proximity to existing roads and availability of resources such as water and cooking fuel will also affect the camp site location optimization process.

5. Conclusion

Mass refugee movement in the form of forced migration can trigger geopolitical chain reactions on a global scale. Dense forest area has decreased from 8531 ha in 2016 to 4498 ha in 2018 and refugee settlement area has increased from 271 ha in 2016 to 2679 ha in 2018. As the results indicate, migration is a direct inducer of deforestation. Deforestation in turn contributes to more environmental impacts. Loss of forests can affect the nutrient cycle in an area, reducing soil fertility/arability of affected lands. Lack of root systems makes affected regions more susceptible to water and wind erosion. Deforestation releases trapped carbon back into the atmosphere, reversing decades of carbon sequestration. Thus, it is evident that the environmental effects of migration and deforestation are not isolated, rather amplified when a region is subjected to migration and deforestation. Until a mutual governmental agreement is reached between Myanmar and Bangladesh, the government and the Forest Department can play a massive role in minimizing the detrimental effects of deforestation. Planned refugee sites which are less susceptible to deforestation can be issued in order to remove pressure from heavily deforested areas. Alternative cooking fuel resources can also reduce wood cutting of forest areas neighboring camp sites. The study can be utilized to estimate carbon stock and environmental economic losses. Due to the temporary and unstable nature of the Rohingya settlements in Bangladesh, the study area is susceptible to poor sanitation and solid waste management. We have attempted to open a new horizon into standardization of study of refugee emergencies which will help to better understand the political ecology of forced migration and deforestation.
Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Nahian Ahmed http://orcid.org/0000-0003-2041-4166
Mohammad Sujauddin http://orcid.org/0000-0001-5913-882X

References

Batterbury, S. (2001). Landscapes of diversity: A local political ecology of livelihood diversification in south-western Niger. Ecumene, 8(4), 437–464.

Black, R. (1994). Forced migration and environmental change: The impact of refugees on host environments. Journal of Environmental Management, 42(3), 261–277.

Black, R., Adger, W. N., Arnell, N. W., Dercon, S., Geddes, A., & Thomas, D. (2011). The effect of environmental change on human migration. Global Environmental Change, 21, S3–S11.

Breiman, L. (2001). Random forests. Machine Learning, 45, 5–32.

Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). Classification and regression trees. Taylor & Francis.

Castles, S. (2003). Towards a sociology of forced migration and social transformation. Sociology, 37(1), 13–34.

Chaaban, J., Ghattas, H., Habib, R., Hanafi, S., Sahyoun, N., Salti, N., . . . Naamani, N. (2010). Socio-economic survey of Palestinian refugees in Lebanon. Report published by the American University of Beirut (AUB) and the United Nations Relief and Works Agency for Palestine Refugees in the Near East (UNRWA), American University of Beirut, 8.

Chander, G., Huang, C., Yang, L., Homer, C., & Larson, C. (2009). Developing consistent Landsat data sets for large area applications: The MRLC 2001 protocol. IEEE Geoscience and Remote Sensing Letters, 6(4), 777–781.

Cheung, S. (2011). Migration control and the solutions impasse in South and Southeast Asia: Implications from the Rohingya experience. Journal of Refugee Studies, 25(1), 50–70.

Choudhury, J. K., & Hossain, M. A. A. (2011). Bangladesh forestry outlook study. In Asia-Pacific forestry sector outlook study II. Bangkok, Thailand: Food and Agriculture Organization.

Chowdhury, M. S. N., Hossain, M. S., Mitra, A., & Barua, P. (2011). Environmental functions of the Teknaf Peninsula mangroves of Bangladesh to communicate the values of goods and services. Mesopotamian Journal of Marine Science, 26(1), 79–97.

Chu, F., Jin, G., & Wang, L. (2005). Cancer diagnosis and protein secondary structure prediction using support vector machines. In L. Wang (Eds.), Support vector machines: Theory and applications (pp. 343–363). Berlin, Heidelberg: Springer.

Churches, C. E., Wampler, P. J., Sun, W., & Smith, A. J. (2014). Evaluation of forest cover estimates for Haiti using supervised classification of Landsat data. International Journal of Applied Earth Observation and Geoinformation, 30, 203–216.

Codjoe, S. N. A., & Bilshborrow, R. E. (2011). Population and agriculture in the dry and derived savannah zones of Ghana. Population and Environment, 33(1), 80–107.

Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine Learning, 20(3), 273–297.

Darmawan, R., Klasen, S., & Nuryartono, N. (2016). Migration and deforestation in Indonesia (No. 19) (EFFoRTS Discussion Paper Series).

Department, F. (2018). Organogram of forest department in Bangladesh. Retrieved April 11, 2018, from http://www.bforest.gov.bd/at/11:24 am.

Fraser, A. I. (1998). Social, economic and political aspects of forest clearance and land-use planning in Indonesia. In B. K. Maloney (Eds.), Human activities and the tropical rainforest (pp. 133–150). Dordrecht: Springer.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google earth engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment, 202, 18–27. doi:10.1016/j.rse.2017.06.031

Grimm, M., & Klasen, S. (2015). Migration pressure, tenure security, and agricultural intensification: Evidence from Indonesia. Land Economics, 91(3), 411–434.

Hammer, T. (2004). Desertification and migration: A political ecology of environmental migration in West Africa. In J. D. Unruh, M. S. Krol, & N. Kliot (Eds.), Environmental change and its implications for population migration (pp. 231–246). Dordrecht: Springer.

Hankins, C. A., Friedman, S. R., Zafar, T., & Strathdee, S. A. (2002). Transmission and prevention of HIV and sexually transmitted infections in war settings: Implications for current and future armed conflicts. AIDS, 16(17), 2245–2252.

Hansen, M. C., Stehman, S. V., Potapov, P. V., Loveland, T. R., Townshend, J. R., DeFries, R. S., . . . DiMiceli, C. (2008). Humid tropical forest clearing from 2000 to 2005 quantified by using multitemporal and multiresolution remotely sensed data. Proceedings of the National Academy of Sciences, 105(27), 9439–9444.

Homer-Dixon, T. F. (1991). On the threshold: Environmental changes as causes of acute conflict. International Security, 16(2), 76–116.

Hugo, G. (1996). Environmental concerns and international migration. International Migration Review, 30, 105–131.

Hunter, L. M. (2005). Migration and environmental hazards. Population and Environment, 26(4), 273–302.

Immitzer, M., Atzberger, C., & Koukal, T. (2017). Evaluation of forest cover estimates for Haiti using supervised classification of Landsat data. Remote Sensing, 4(9), 2661–2693.

IRIN. (2008). Rohingya refugee camps improved. Retrieved April 11, 2018, from http://www.irinnews.org/news/2008/11/07/rohingya-refugee-camps-improved-at-11:35 am

ISCG. (2018). Location of Rohingya refugees in Cox’s Bazar. Retrieved March 1 2018, from https://data.humdata.org/dataset/site-location-of-rohingya-refugees-in-cox-s-bazar

Kalipeni, E., & Oppong, J. (1998). The refugee crisis in Africa and implications for health and disease: A political ecology approach. Social Science & Medicine, 46(12), 1637–1653.

Kibreab, G. (1997). Environmental causes and impact of refugee movements: A critique of the current debate. Disasters, 21(1), 20–38.

Klasen, S., Faust, H., Grimm, M., & Schwarze, S. (2010). Demography, development, and deforestation at the rainforest margin in Indonesia. In Tscharsntke T., C.
