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IMPACT OF ROHINGYA SETTLEMENT ON THE LANDCOVERS AT UKHIYA UPAZILA IN COX' S BAZAR, BANGLADESH

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Abstract

The Ukhiya Upazila is an environmentally critical area where more than seven hundred thousand Rohingya refugees have temporarily settled since August 2017. The site is facing numerous land cover changes due to anthropogenic pressures exerted by the Rohingya resettlement program. The research measures the delineation of land cover in study area due to the 2017 forced migration of Rohingya refugees from Myanmar. In this research, the GIS-post processing classification approach is performed on Landsat images for five time periods (1980, 1990, 1999, 2010, and 2020) to identify the land cover change in the study area. From 1980 to 2020, more than 14.34 sq. km. of agricultural land increases, and 42.93 sq. km. of greenery was reduced due to anthropogenic activities. Furthermore, four classification approaches (GIS post-processing, OBIA, supervised, and unsupervised) was used to identify precise land cover classification method where GIS post-processing method seemed to be a suitable approach for land cover classification. The Kappa aspect shows that the post-processing GIS method can minimize most errors in the classifying procedure. The research will help the policymakers to identify the changes made on the land covers. The identified changes will be the key to determine the financial and ecological losses to claim compensation in the future.

Keywords: *Rohingya migration, Land cover, GIS-post processing, OBIA*

Introduction

The function of anthropological action on the earth's surface is defined by land use, and visible land use characteristics on the world's body are determined by the land cover (Weihand White, 2008; Zhang *et al.* 2009 and Rai *et al.* 2017). Timberlands, pastures, water bodies, crops, and settlements are illustrations of land cover (Slonecker*et et al.* 2013). Again, land cover changes are characterized by altering the earth's upper surface (Sealey *et al.* 2018) and have many local, regional, and global environmental, physical, and socio-economic consequences (Pellikka *el al.* 2013 & Slonecker *et al.* 2013). The management of natural resources and monitoring of ecological changes, land use and land cover (LULC) data play a significant part (Kaul and Sopan, 2012 & Salih, 2018).

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Spatial intelligence technology, such as remote sensing with satellite imagery, can produce precise LULC maps in a brief time (Srivastava *et al.* 2012). One of the most significant applications developed from Earth observation satellites is the LULC classification of Landsat images (Phiri and Morgenroth, 2017). Landsat images are free data and comprise multispectral bands; therefore, it is widely used for different kinds of land cover recording (Xie*et et al.* 2019). However, the spatial resolution of imageries, data time, data source, classification procedure, different software, and human errors during training sample selection make LULC classification more complicated (Li *et al.* 2012). Therefore, a suitable classification method requires a comparative study of various classification methods (Lu *et al.* 2003). Although, all classification approaches (e.g., sub-pixel, knowledge-based, contextual-based, unsupervised and supervised classification methods, object-based image analysis (OBIA) and hybrid method) are not fully automated and have strengths and limitations (Phiri and Morgenroth, 2017). As a result, it remained to be answered, which LULC classification procedure would be applied to a specific dataset in a study area (Li *et al.* 2012). One of the most critical tasks for image classification is to assess the precision of classified maps; without accurate assessment, the statistical result of classified images is less valued to the end-user (Bharatkar and Patel, 2013). Again, error matrix or confusion matrix and kappa-based accuracy assessment are widely used for image classification accuracy assessment (Foody, 2008). The standard kappa coefficient, overall accuracy, producer's accuracy, and user's accuracy are encompassed in the kappa-based accuracy method, where overall accuracy is the fraction of precisely classified samples (Verma *et al.* 2020)

In the last few decades, South Asian countries experienced a drastic change in LULC due to the rise of cropland and fall of forest cover (Rai *et al.* 2017). Bangladesh has experienced rapid LULC changes over the past few decades due to the rapid increase of population, economic growth, and climate change impacts (Sajib, 2018). In addition to these factors, Rohingya refugees' forced migration has created an instantaneous effect on the southeastern part of Bangladesh's forested area in recent years.

The Rohingya refugees living in Cox's Bazar district of Bangladesh are Myanmar's ethnic, religious, and linguistic minority (Lew, 2010; Kipgen, 2013; UNHCR, 2016 and Quader *et al.* 2020). In Myanmar, they gradually faced exclusion, particularly since the military takeover in 1962 (Sarkerand Rodrigo, 2014). The mixture of constraints and violence has profoundly affected their economic survival (Mollah*et et al.* 2004). Apart from this, the Rohingya people face ethnic cleansing by the Buddhist majority in Myanmar, forcing them to flee in search of relative safety in Bangladesh's neighboring country (Hassan *et al.* 2018). An estimated 1,389,753 Rohingya refugees fled to Bangladesh from 1978 to 2018 (Amnesty International, 2004; UNDP Bangladesh and UN WOMEN Bangladesh, 2018). However, few from 1978 migration returns due to

international pressure on Myanmar (Amnesty International, 2004). But the last influx of Rohingya refuge (2017-2018) has created a humanitarian emergency in Cox's Bazar district (UNDP Bangladesh and UN WOMEN Bangladesh, 2018 and GFDRR, 2018). The majority of this population settled in makeshift camps, replacing forested hills surrounding the two existing refugee camps located in Kutupalong and Nayapara in Ukhiya and Teknaf Upazila, respectively (Hassan *et al.* 2018). The speed and scale of the influx have resulted in a critical environmental emergency. Various estimates suggest that approximately 4000 acres of forested hills in the study area cleared to erect makeshift camps since August 2017 (Hossain, 2018), reflecting an annual loss of roughly 412,14331 BDT (Labib *et al.* 2018). The continuously increasing population impacts the local forest resources and the ecosystem (Imtiaz, 2018) and increases the land surface temperature (Rashid *et al.* 2020).

The pressure of a large number of Rohingyas on the land covers and the long-lasting natural settings of Ukhiya Upazila is enormous. The modifications made by the Rohingya settlement and their activities are worth documenting. Several studies have been conducted on forest cover losses due to the influx of Rohingya refugees, which estimate a minimum of five years to a maximum of thirty years of change (Hassan *et al.* 2018; Imtiaz, 2018; Labib *et al.* 2018; Rahman *et al.* 2018; Quader *et al.* 2020; Rashid *et al.* 2020 and Hasan *et al.* 2020). Moreover, the majority of the study gives priority to change vegetation cover only. But no study evaluates the land cover change of the Ukhiya Upazila for more than 30 years. The first attempt to assess land cover changes in Ukhiya Upazila in the last 40 years (1980-2020). The research's main objective is to identify the impact on the land cover of the Rohingya migration. In addition to this, the study also evaluates the multi-classification approach to the performance of land cover identification on multi-sensor satellite images.

Material and Methods

Study Area

Ukhiya is an Upazila (Fig. 1) of Cox's Bazar district has been selected as the study area considering the location, refugee population, number of camps, and the impact of the makeshift settlement on the land cover. It is situated between 21°08' and 21°21' N latitudes and in between 92°03' and 92°12' E longitudes. Ukhiya Thana was established in 1926 and became an Upazila in 1983 (Chowdhury, 2012). It shares administrative boundaries on the north by Ramu Upazila, south by Teknaf Upazila, Arakan state of Myanmar, and Naikhongchhari Upazila on the east, the Bay of Bengal on the west. The total area of the district is 261.80 sq. km. out of which 155.14 sq. km. are reserve forests. The riverine area covers .91 sq. km. where the main river is the Naf River. The Reju Canal and Enani sea beach are recognizable for their tourist attraction (BBS, 2013). The vast majority of Rohingya refugees living in Ukhiya Upazila are women and children, where over 60% and 40% are children under 18 and 12 (UNHCR, 2020 & OXFAM,

2020). The total household is 152908, and the population size is 700577 in 26 refugee camps of Ukhiya Upazila (HDX, 2020a).

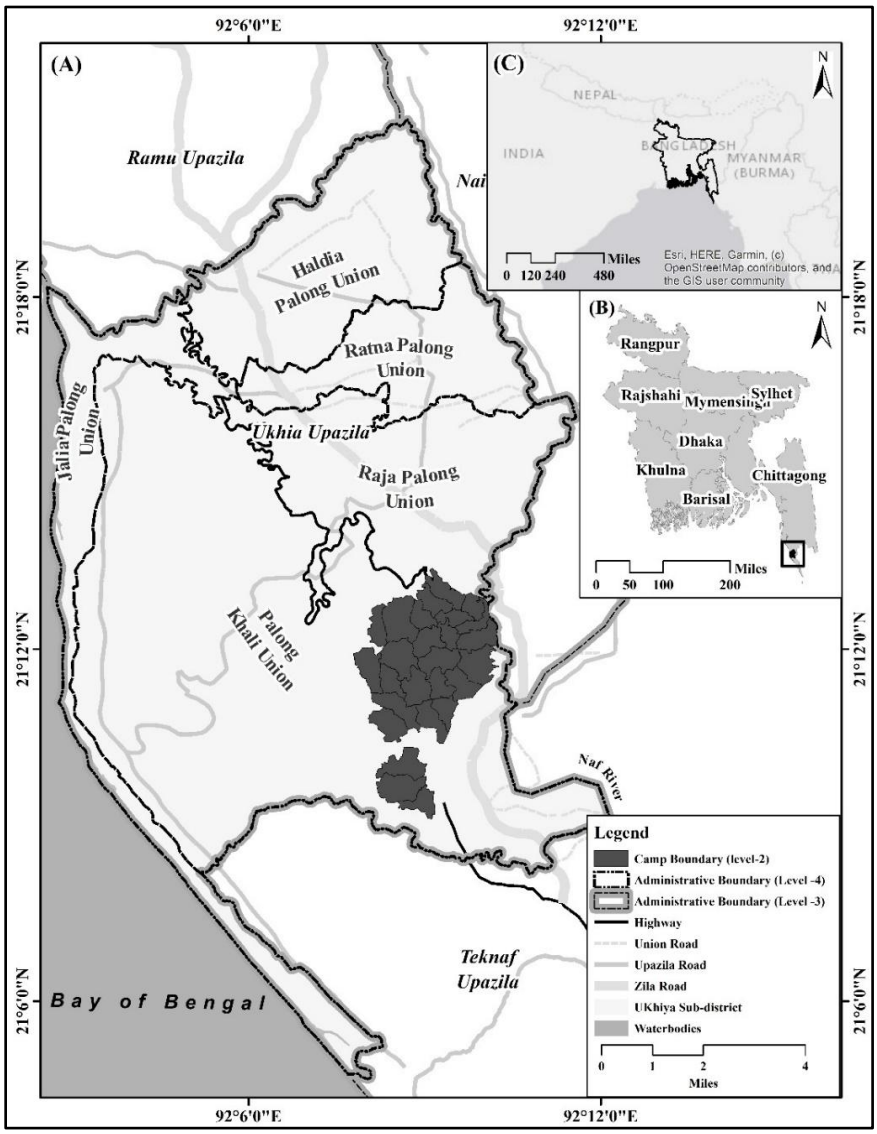

Figure 1. The Study Area; In figure index map (A) shows the location of Ukhiya Upazila[Gray Color (10%)] and Kutupalog Refugee camp [Gray color (70%)], which shares a border with the Bay of Bengal in the west, Teknaf in the south, Ramu in the north and Myanmar in the east. The index map (B) shows the location of Ukhiya Upazila (Black rectangle) in Bangladesh. Lastly, the index map (C) shows the location of Bangladesh in the world.

Data Source and Pre-processing

Five scenes of various Landsat sensors (e.g., MSS, TM, OLI/TIRS) data were used in this research. The satellite imageries were acquired from the USGS Global Visualization Viewer website (www.usgs.gov.in) for a total of five years (e.g., 1980, 1990, 1999, 2010, and 2020) with less than .10 cloud cover (Table 1). All satellite images were obtained between the end of October and the beginning of February. We used composite combinations of B4 (Band 4 = Green; Wavelength = 0.5-0.6), B5 (Band 5 = Red; Wavelength = 0.6-0.7), B6 (Band 6 = Near-Infrared; Wavelength = 0.7-0.8), and B7 (Band 7 = Near-Infrared; Wavelength = 0.8-0.11) for Landsat 3 image, where Near-Infrared Band B7 give more emphasis on vegetation boundary between land and water compared to Near-Infrared Band B6. Again for Landsat 5 and Landsat 7 images following order band B1, B2, B3 and B4 (Band 1 = Blue; Wavelength = 0.45-0.52, Band 2 = Green; Wavelength = 0.52-0.60, Band 3 = red; Wavelength = 0.63-0.69; Band 4=Near-Infrared; Wavelength = 0.77-0.90) are used for final image by using composite bands tool in ArcMap 10.7 software. Composite tired for 2020 images (Landsat 8) are B2, B3, B4, and B5 (Band 2 = Blue; Wavelength = 0.45-0.52, Band 3 = Green; Wavelength = 0.52-0.60, Band 4 = Red; Wavelength = 0.63-0.69; Band 5 = Near-Infrared; Wavelength = 0.84-0.88). After layer stacking the bands, each image was clipped by Ukhiya Upazila administrative boundary using raster processing tools in ArcMap 10.7 Platform. The Ukhiya Upazila and Rohingya refugee camps administrative boundary shape file has been collected from the HDX website (HDX 2020b & HDX 2020c).

Table 1. Features of remotely sensed and spatial data used in the study.

Sensor	Platform	Acquisition Date (yyyy/mm/dd)	Spatial Resolution (m)	Path	Row	Cloud Cover
MSS	Landsat 3	1980-02-01	60	136	45	0.00
TM	Landsat 5	1990-10-31	30	136	45	0.00
ETM	Landsat 7	1999-12-19	30	136	45	0.00
TM	Landsat 5	2010-02-08	30	136	45	0.00
OLI/TIRS	Landsat 8	2020-02-20	30	136	45	0.08
Administrative Boundaries	HDX	2015	-	-	-	-
Rohingya camps	HDX	2020	-	-	-	-

Note: The images were spatially referenced in the Universal Transverse Mercator (UTM) projection system (zone 46 north) with the World Geodetic System (WGS) 1984 as the datum.

Image classification

In this study, a GIS-post processing approach was adopted to identify the land cover changes at Ukhiya Upazila. This approach combines the unsupervised, supervised, and OBIA (object-based image analysis) classification method. These three methods have been incorporated by ArcMap 10.7 platform with advanced overlay and editing tools. A total of five land cover classes (agricultural land, barren land, settlements, vegetation, and water bodies) were selected for land cover classification (Table 2).

Table 2. Classes delineated based on the GIS-post processing approach for 1980, 1999, 2000, 2010, and 2020.

Class Name	Description
Agricultural Land	Crop field
Barren Land	Abandoned field
Vegetation	Rural and urban vegetation, Forest
Settlement	Roads, rural and urban settlements
Waterbodies	Open water, pond, sea, canals, and rivers

Four approaches (object-based, unsupervised, supervised, and GIS post-processing) were used on Landsat 8 (OLI/TIRS) image of 2020 of the study area to identify the best method for LULC classification. Ninety training samples (15 samples for each class) were selected for supervised classification in ArcMap 10.7. In unsupervised classification, sixty classes were chosen for LULC classification, and later this recodes into five classes. For the OBIA segmentation process, we used the multi resolution segmentation algorithm with a pixel-level domain in eCognition developer 9.0 software. The scale parameter was 10, shape (define the weight the shape criterion should have when segmenting image) and compactness (determine the importance of the compactness criterion, the higher the value, the more compact image objects) was 0.1 and .98, respectively. ArcMap 10.7 software was used for computing each land cover class.

Accuracy Assessment

An auto accuracy assessment was conducted to prepare kappa coefficients, producer's accuracy, user's accuracy, and overall accuracy from the output map through the ArcGIS 10.7 platform, where 100 samples were selected randomly compared with reference data for image 2020. The 100 samples were verified with Google Earth's historical images on 01/20/2020 (combined images of 2020 Google US Dept. of State Geographer image, 2020 Maxer Technologies Images, and 2020 Terra Metrics) using Google Earth Pro software.

Results and Discussion

The increasing population, urbanization, and forced migration of refugees from Myanmar have increased the settlement, directly impacting the study area's land cover (Ahamed *et al.* 2020; Quader *et al.* 2020).

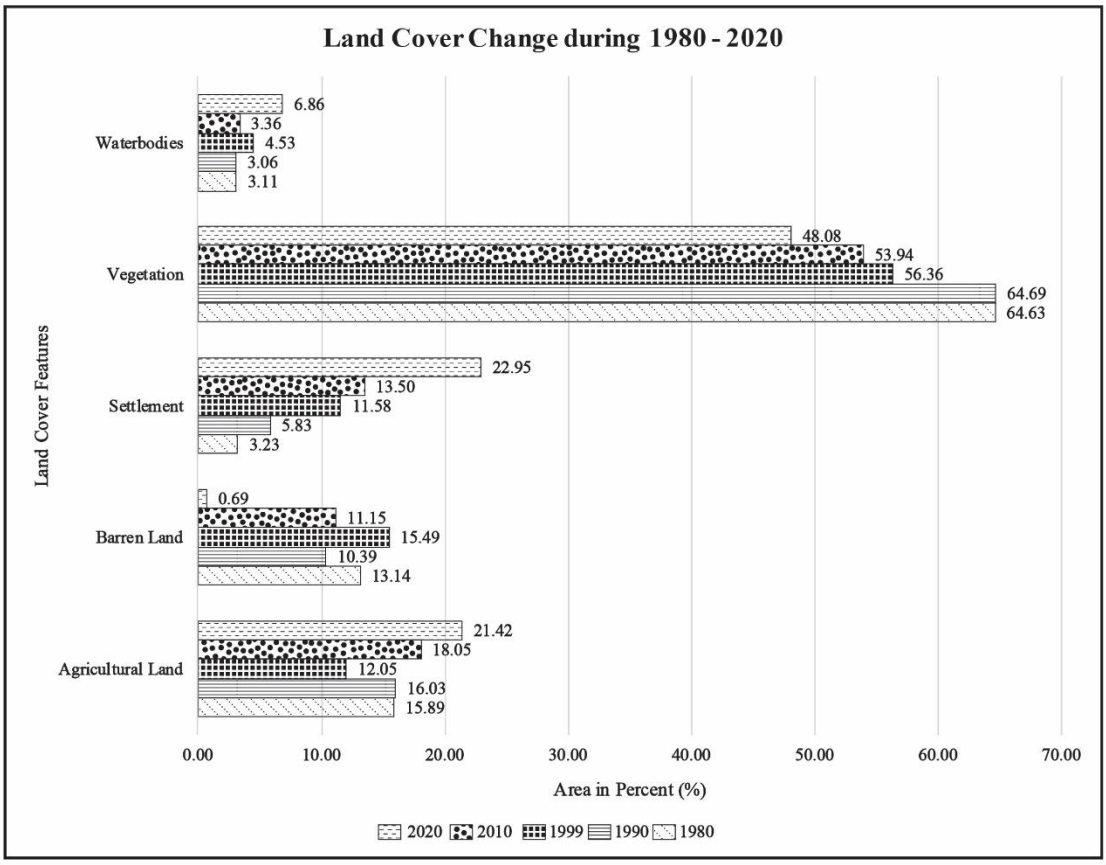

Figure 2. The land cover features in percentage from 1980-2020.

Fig. 2 shows the summarized bar graph of the land covers (agricultural land, barren land, settlements, vegetation, and water bodies) in percentages with different periods. Fig. 3 shows the land cover thematic maps from 1980 to 2020 of the study areas. A significant change was observed in the farming land cover area (Fig 3a and Fig 3e), accounting for more than 14% of agricultural land increases in the study area. Due to the Rohingya refugee influx, a large portion of agricultural land turned into a temporary settlement area in the Kutuplong camp area (Quader *et al.* 2020). The size of the barren land decreased to 1.80 sq. km. (0.69 percent of entire land) in the gap of 40 years interval.

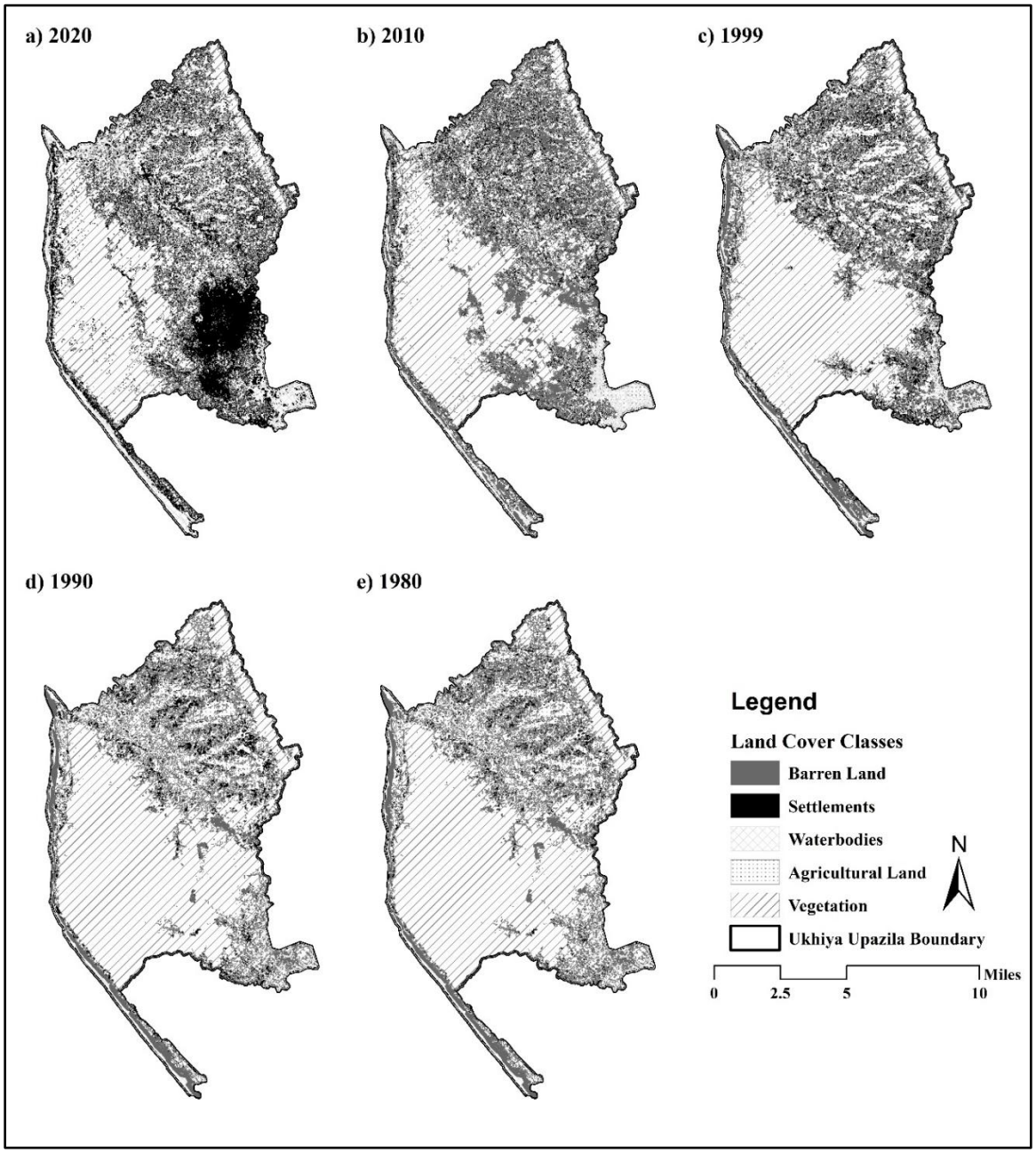

Figure 3. Land cover maps of 2020, 2010, 1999, 1990, and 1980. In Fig. 2, Graycolor (60%)and Black color show the Barren land and settlements land cover, respectively. Waterbodies, agricultural land, and vegetation illustrate by crosshatch, ordered stipple, and sample hatch symbols.

Again, 51.12 sq. km of new settlement areas were observed from 1980 to 2020 in Ukhiya Upazila. Similar upward settlement land cover result for the study area found by Alam *et al.* 2020 and Ahamed *et al.* 2020 in their research; however, their AOI (Area of interest) is different from the present study. The vegetation cover of the study area contains homestead vegetation and forest area. The dominant vegetation cover in the study area was observed in the 1980 classified image (Fig. 3e). Again, after eight years (1988), thick vegetation cover witnessed in NDVI (Normalized difference vegetation index) result in the Ukhiya Upazila (Rahman *et al.* 2018). In the last 40 years, 16.35% of vegetation was reduced in the study area due to increased agricultural land and settlements. But the most concerning thing is that 15.20% of the vegetated area that accounts for 3939 hectares of land vanished over the previous three years (2015-2018) (Quader *et al.* 2020). Again, this vegetation cover plays a vital role in the adaptation and migration process of climate change in Bangladesh's southern coastal part (Imtiaz, 2018). Therefore, this area is denoted as an ecologically critical area (ECA) (Rahman, 2019; Hasan *et al.* 2020). On the other hand, the water bodies area expended from 1980 to 2020.

Table 3. Impact of classification approaches in the spatial extent of land cover.

Land Cover features	Classification Type			
	GIS post-processing	OBIA	Supervised	Unsupervised
	Area in percent (%)			
Agricultural Land	21.41	21.03	17.21	18.74
Barren Land	0.69	1.47	9.56	6.23
Vegetation	48.07	47.30	54.20	67.12
Settlements	22.95	23.72	8.95	6.23
Waterbodies	6.84	6.48	10.08	1.65

Note: Four classification approaches have been adopted for classifying the 2020 satellite image using ArcMap 10.7 and eCognition developer 9.0 software.

Table 3 illustrates the land cover area in percentage for OBIA, supervised, unsupervised, and GIS post-processing classification for 2020 satellite image. Fig. 4 displays thematic maps of this classification approach. There is a slight gap observed in the statistical result of agricultural land cover class between OBIA and GIS-post processing approaches. GIS-post processing and OBIA classification result for the agricultural land cover is 21.41% (with 90% producer and user accuracy) and 21.03% (with 90% producer accuracy and 82% user accuracy) (Table 4), respectively. GIS post-processing approach provides more accurate mapping because it's a combination of multi-approach (Thapa and Murayama, 2011). However, various researches have shown outstanding results of an object-based approach to image analysis.

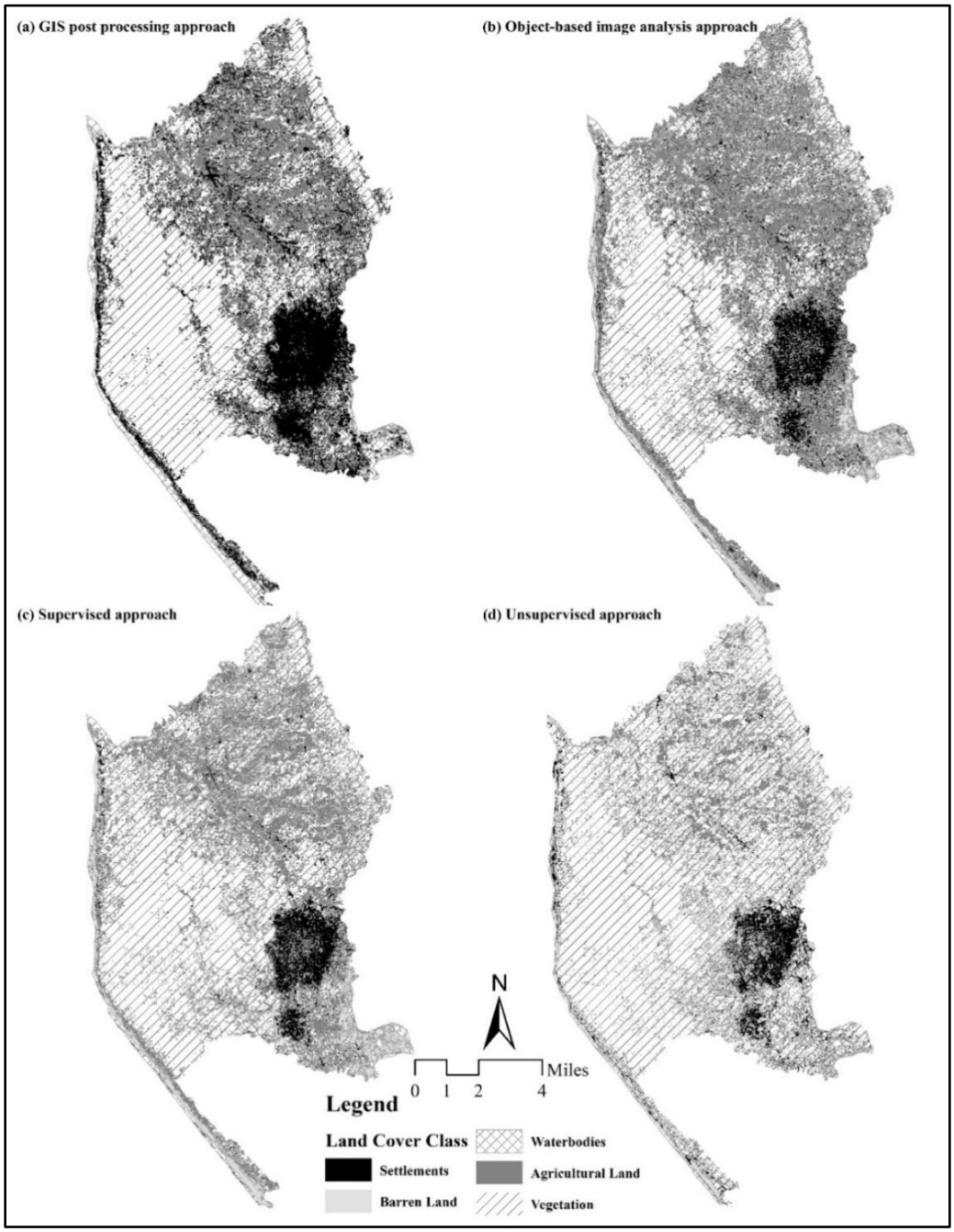

Figure 4. Land cover maps developed by different classification approaches. Black color, Gray (10%), Crosshatch, Gray (50%), Simple hatch denotes settlement, barren land, water bodies, agricultural land, and vegetation land cover respectively in the map.

Still, this system's main obstacle is selecting the optimal segmentation scale and the low spatial resolution of satellite imagery (Phiri and Morgenroth, 2017). On the other side, supervised and unsupervised illustrates that agricultural land cover is 17.21% (with 80% producer accuracy and 73% user accuracy) and 18.74% (with 70% producer accuracy and user accuracy). Both approaches are standard programmed computer classification systems (Zhang *et al.* 2009) and widely used in remote sensed-based research. For the barren land cover, the GIS-post processing approach presents 90% producer accuracy, which is highest than the other classification approach. Similar statistical results (both producer accuracy and user accuracy) for vegetation and water body classes show in the supervised and unsupervised classification method. However, optimum producer and user accuracy (up to 90%) displays for GIS post-processing and OBIA classification method. Again, for the settlement class, GIS post-processing approach and supervised, indicating the highest and lowest statistical results, respectively.

Table 4. Overall accuracy and Kappa statistics of the GIS-post processing, OBIA, supervised, and unsupervised classification approach for land cover classification.

Classification Approaches	Classes										Overall accuracy (%)	kappa statistics
	AL		BL		V		S		WB			
	PA (%)	**UA** (%)	**PA** (%)	**UA** (%)	**PA** (%)	**UA** (%)	**PA** (%)	**UA** (%)	**PA** (%)	**UA** (%)		
GIS Post-processing	90	90	90	82	100	100	90	100	100	100	94	0.93
OBIA	90	82	70	88	90	100	90	90	100	83	88	0.85
Supervised	80	73	50	83	90	69	60	67	90	82	74	0.68
Unsupervised	70	70	40	67	90	69	70	70	90	82	70	0.63

Note: (**AL**- Agricultural Land, **BL**- Barren Land, **V**- Vegetation, **S**- Settlements, **WB**- Water Bodies; **PA**- Producer Accuracy, **UA**- User Accuracy). Accuracy assessed is based on 100 random points collected from the 2020 Google Earth image of the selected area.

The overall precision of the GIS post-processing, OBIA, supervised, and unsupervised classification of 2020 images ranges from 70% to 94% (Table 4). A total precision of 94 percent was shown in the GIS post-processing approach, which is close to the overall accuracy (88 percent) of the OBIA method. The unsupervised method scores the most flawed accuracy in all modes. The kappa indices illustrate a clearer picture. The kappa score is 0.93, 0.85, 0.68, and 0.63 for the GIS post-processing approach, OBIA method, supervised method, and unsupervised method, respectively. A kappa score of up to 0.70 is regarded as a sign of an outstanding level of agreement with validation data (Quader *et al.* 2017).

Conclusion

The Rohingyas are an ethnic, religious, and linguistic minority in Myanmar who primarily inhabit the three townships of North Arakan, which borders Bangladesh. They face ethnic cleansing by the Buddhist majority in Myanmar, forcing them to flee in search of relative safety in Bangladesh. The study illuminates Rohingya's impact on the land covers in the Ukhiya sub-district of Cox's Bazar. The study showed land cover dynamics from 1980 to 2020 over the study area. Between 1980 to 2020, vegetation cover increase from 41.19% to 55.53%. The majority of the vegetation area is converted to agricultural land and settlements purpose. The various change in land cover observes after the 2017 Rohingya influx. The study found that the settlement cover increase rate between 1980-2010 (26.61%) is the same as the last ten years (1999-2020), which is 24.51%. The upward momentum of settlement not only impacting local inhabitant's regular life in the study area also causing severe environmental degradation (Hasan *et al.* 2020). Again, in classification procedure, GIS post-processing and OBIA system exhibited strong producers' accuracies in all groups (over 80 percent average). Both the post-processing GIS approaches and the OBIA approaches did the best to extract land overs, as both the accuracies of their producer and user were strong. The Bangladesh government has set an example of humanity by giving shelter to the Rohingya people. But this shelter is already beyond the capacity of this country. The international community should exert more pressure and play a sensible role to help Rohingya's safe and voluntary exit.

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