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RESEARCH ARTICLE

Artificial Neural Network-Based Land Use-Specific Carbon Patterns and Their Effects on Land Surface Temperature as a Result of the Rohingya Refugee Influx

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ABSTRACT The objective of the research is to investigate how refugees' influx has altered the carbon dynamics of different land uses and the relationship between land use specific carbon emissions and land surface temperature (LST). Two upazilais of the Cox's Bazar district, Bangladesh (i.e., Ukhiya and Teknaf), were mostly affected by the Rohingya refugee influx and are the focus of the study. The study classified the land use land cover (LULC) into four classes (e.g., agricultural, forest, settlement, and water) for two different time periods (i.e., before and after the influx of Rohingya refugees) using an artificial neural network algorithm and sentinel satellite imagery. Carbon emissions and absorptions specific to land use were calculated using classified land use land cover and coefficients. Again, two time series of Landsat 8 imagery were applied to estimate land surface temperature shifts. The area of forests was found to have decreased by 21.19 square miles (9.58 percent) and the area of settlements to have increased by 18.24 square miles (8.25 percent) between 2017 and 2021. There was a negative net land-use based carbon emission of -5187.02 tons per year in 2017. In 2021, it was predicted that annual net emissions would total 2208.24 tons. LST during the study period has increased as a result of human activities that release greenhouse gases into the atmosphere. The findings of this research will inform policymakers' decisions about the conservation and sustainable development of natural resources in the region experiencing an influx of Rohingya refugees.

INDEX TERMS Carbon emissions, land surface temperature, land use land cover, remote sensing, Rohingya refugee.

I. INTRODUCTION

ABOUT one million Myanmar citizen- Rohingya migrants have sought safety in Bangladesh after fleeing Myanmar's violence and persecution in 2017 [1]. Bangladesh's government in cooperation with international community has extended unprecedented humanitarian support to these Rohingya refugees of Myanmar. The vast majority of Rohingya refugees took shelter and settled in southern part of forested hilly district- Cox's Bazar of

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Bangladesh, located just few km from Myanmar's western border. To accommodate such a big influx of Rohingya refugees within a short time naturally grown forestland were cleared and sheltered were built mostly in an unplanned and uncontrolled manner. About sixty thousand refugees are settled in every square kilometer area which has creased both physical and ecological impacts on the local environment and ecosystem. Some of the studies already warned that continued damage of environment and ecosystem components including water bodies, forest, land, paddy field would have severe long term consequence extending beyond Cox's Bazar region- the key tourist destination of Bangladesh.

At the moment due to rapid land use transformation, the release/emission of greenhouse gases (GHGs) are rampant [2]. In fact, emission of greenhouse gases are currently of great concern due to multiple environmental changes [3]. Sheltering Rohingya refugees has resulted in increased carbon dioxide emissions and environmental degradation. On the other hand, global temperatures are rising as a result of the rise in GHG emissions, both directly and indirectly. The carbon concentrations in the atmosphere have risen between 280 to 450 parts per million of CO_2 equivalent [4]. The Intergovernmental Panel on Climate Change (IPCC) predicts that global temperatures will climb by 1.1-6.4 degrees Celsius this century, with Bangladesh experiencing increases of 1.1–1.5 degrees Celsius by 2050 [5]. Carbon emissions (CEs) are increasing, and the damage they bring to the environment and human health, as well as the Earth's surface temperature but also global average temperature, is concerning [6]. CEs have been blamed by scientists, engineers, and environmentalists for the enormous rise in land surface temperature (LST) and subsequent global warming [7]. The LST in Rohingya refugee influx area is directly affected by land use land cover (LULC) changes resulting from sheltering and associate services to Rohingya refugees. Increasing levels of LST could have numerous negative impacts on the natural environment and micro-climate [8]. The biotic environment of that particular region may also be affected by an increase in LST [9]. Therefore, it is critical to understand how LST fluctuates/changes in response to massive land use transformation, particularly vegetation removal in the host areas of Cox's Bazar. Due to the arrival of Rohingya refugees in Ukhiya and Teknaf areas of Cox's Bazar, vast vegetation coverage has been lost; LST shifting in relation to this loss of vegetation is obvious.

This research has investigated the impact of unplanned and unregulated Rohingya refugee shelters on the physical and ecological aspects of their surroundings. By analyzing satellite images from different time periods, the study has estimated the influence of the refugee settlements on land use-specific CEs patterns and dynamics in LST. The findings of this study have important implications for the conservation and sustainable development of natural resources in the area affected by the Rohingya refugee influx. The results highlight the nexus between CEs and LST, and demonstrate how the presence of refugee settlements has altered land use patterns and increased the temperature of the surrounding environment. These insights can help inform government authorities on the need for better planning and management of refugee settlements to mitigate their impact on the environment. By implementing conservation and sustainable development measures, such as reforestation and sustainable agriculture practices, the authorities can ensure the long-term health of the ecosystem while providing a safe and dignified environment for refugees. Overall, this research sheds light on the complex relationship between human migration and environmental sustainability, and emphasizes the need for collaborative efforts to address these pressing global challenges. The scientific question addressed in this research is: How has the influx of Rohingya refugees affected the carbon dynamics of different land uses and the relationship between land use-specific carbon emissions and land surface temperature in the Cox's Bazar district of Bangladesh?

II. RELATED STUDIES

Several related studies have been performed to show a link between LULC, CEs and LST in the context of several cities in Bangladesh like Kafy et al. [10], Imran et al. [11] on Dhaka, Gazi et al. [12], Abdullah et al. [13] on Chittagong, and Moniruzzaman et al. [14], and Fattah et al. [15] on Khulna city. Numerous studies have shown consequences of Rohingya refugee settlers. Some studies focused on Rohingya refugees and changes in forest cover (for example, [16], [17]), studies on the potential effect of Rohingya refugees on other forms of land cover are also emerging (see, for example, [18], [19]). LULC changes have an influence on ecosystem service functionality in the Rohingya refugee influx area [20], [21], [22]. A set of studies have also linked Rohingya refugee influx on aboveground biomass [19], human-elephant confrontations [23], socioeconomic and environment status [24], and LST in the Rohingya camp area [17]. Works done by [17], [25], and [26] have showed the relationship between vegetation and LST across the Rohingya camp. However, there is a noticeable lack of research that has examined the connection between LULC specific CEs and LST in Cox's Bazar after the massive influx of Rohingya refugees.

This research aims to address a significant gap in knowledge by examining the complex interplay between LULC changes, CEs, and LST in the Cox's Bazar region following the influx of Rohingya refugees and it aims to fill this gap. This study tried to illustrate the shifting patterns of LULC, CEs, and LST, as well as identify the influence of the CEs pattern on LST in the Rohingya refugee influx area. This study's research strategy is not clearly stated to be based on a specific hypothesis. However, the study adopts an artificial neural network approach for land use classification and estimates land surface temperature variations using satellite imagery data (sentinel and Landsat). The research design is most likely based on remote sensing, land cover change analysis, and carbon cycle dynamics. The research discussion section likely responds to the following questions:

(1) How has the influx of Rohingya refugees impacted the land use and land cover of the study area?

(2) What are the specific carbon emissions and absorptions associated with different land use types in the study area?

(3) How has land surface temperature changed over time and what are the factors contributing to these changes?

(4) What are the potential implications of these findings for policymakers in terms of conservation and sustainable development of natural resources in the study area?

Based on the research questions specific objectives of the study are: (i) to estimate the influence of the Rohingya refugee influx on artificial neural network (ANN)-based LULC-specific CE patterns and LST dynamics; and (ii) to examine the nexus between CEs and LST in the Rohingya refugee influx area. This is the first study to show a nexus between three important factors such as ANN-based LULC, CEs, and LST in the Rohingya refugee influx area. Previous studies did not include the Rohingya influx's impact on LULC-specific CEs, which makes the study different and unique than the previous one. This study can help demonstrate the connection between LULC changes, CEs, and LST in Cox's Bazar after the influx of Rohingya refugees. By analyzing the specific LULC patterns associated with carbon emissions and their relationship to LST, the study can shed light on the factors that contribute to carbon gas emissions and urban heat island effects in the region. Ultimately, the findings of the study can help policymakers regarding carbon emissions and land use, as well as contribute to the development of more effective strategies for managing the local environment and mitigating the effects of the massive Rohingya refugee influx.

III. MATERIALS AND METHODS

A. DESCRIPTION OF STUDY AREA

South-east Bangladesh's coastal areas (namely the district of Cox's Bazar) are particularly at risk from the effects of the Rohingya influx [27]. Most Rohingya refugees entered Bangladesh in 1991, 2012, and 2017. A total of 914,998 Rohingya refugees (34.917 registered and 880,133 counted) were seeking asylum in Bangladesh as of 30 September 2019 [28]. Teknaf and Ukhiya upazilas in Cox's Bazar district are selected as study area where the majority of Rohingya refugee camps are located. Hilly terrain, flat piedmonts, tidal floodplains, and a 120-kilometer stretch of beach along the Bay of Bengal (the world's longest beach) all contribute to the region's varied topography. Partially wooded slopes ranging in height from 100 to 250 meters rise on left side of this stretch of coastline. Gently sloping land along the foothills is known as the "piedmont plains," where people tend to congregate on a regular basis. These flatlands, which account for 31% of the total land area, have a maximum height of 10 meters and are generally found on the western, eastern, and southern sides of the hills that run north to south along the peninsula's northern and southern borders. The 3155 hectares of sandy beaches along the peninsula's western shore near the Bay of Bengal account for 9.03 percent of its total area. The average altitudes vary from 5 to 55 meters. Figure 1 depicts the location of the research region.

B. DESCRIPTION OF MATERIALS

Sentinel-2A and Sentinel-2B, 2 high multispectral satellites which provide pictures with a spatial resolution of 10 m with in visible and the near-infrared (NIR) bands, have contributed significantly to our present knowledge of land cover. Sentinel satellite images from two separate time periods were collected for the study area: before the influx (before August 25, 2017) and after the influx. As object analysis from images taken during the monsoon's rainy season (March–November) is difficult, we used clear Sentinel-2A satellite image of January 2017 and a Sentinel-2B post-event image of January 2021 (see Table 1) from European Space Agency (https://glovis.usgs.gov/).

A total of 800 sample sites were selected randomly for this study using field observations and WorldView-2 images with a spatial resolution of 0.5 m. However altogether 640 samples from 80 percent of the sample sites were utilized for training sample, while 20 percent (160 samples) were used for test data. The sample sites were divided into four LULC categories: agriculture, forest, settlement, and water (See Table 2). Two time series of Landsat 8 Operational Land Imager (OLI) pictures (path/row 139/43) downloaded from the United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov) were used to estimate changes in land surface temperature. For information on the camps that house Rohingya refugees, the United Nations High Commissioner for Refugees was contacted. These photographs were taken for the pre-influx period (January 2017) and the post-influx era (January 2021) [28].

C. ANN MODEL FOR LULC CLASSIFICATION

Parameter retrieval and LULC changes are examples of non-linear phenomena for which the ANN is the most extensively used machine-learning method. It is also capable of handling large datasets. For non-parametric classification, it is one of the most commonly used techniques [29]. It does not rely on the premise that the data is widely available [30]. For the forging reasons we have used the ANN techniques of Machine learning method.

Back propagation algorithm was used to train the ANN, which is a forward structure black-box model (supervised training algorithm). One way to think of an ANN is as an artificial human brain or nervous system, with nerve fibers connected to one another via other axons [31]. Even if the supplied data contains errors or is complex and incomplete, it can still learn from examples and give useful findings. Because of this, it is able to mimic the human nervous system in every way possible. There are three layers in a neural network: input, hidden (at least one), and output. However,

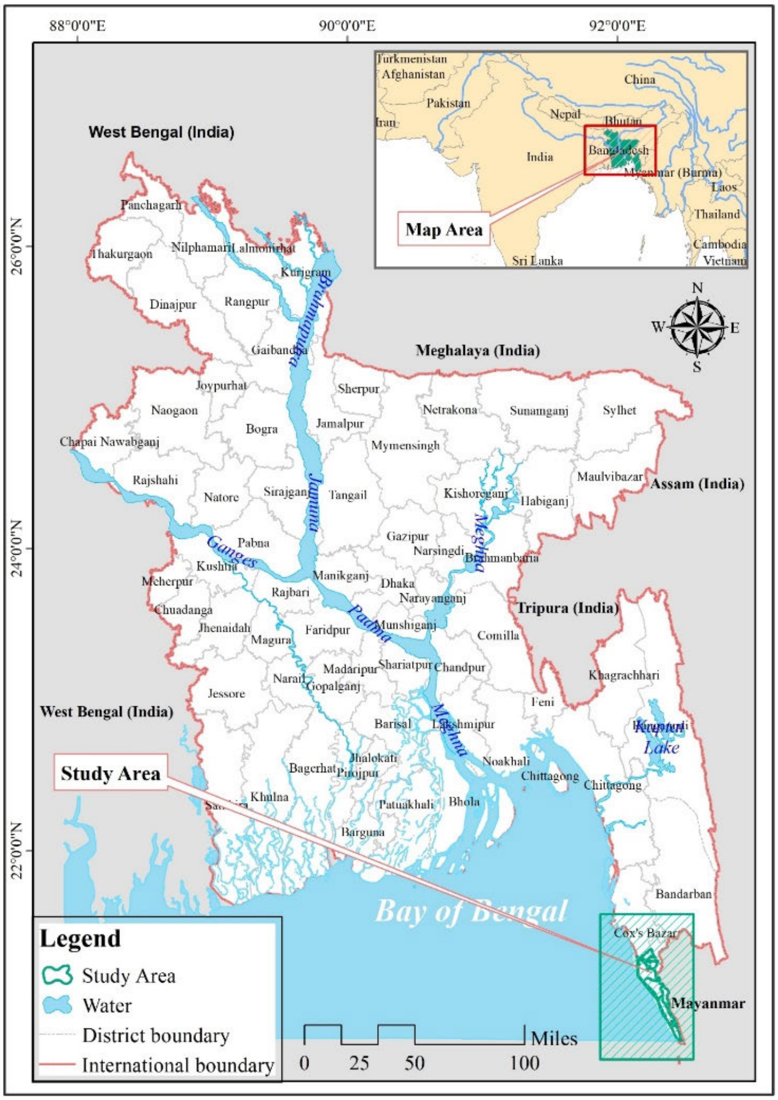


FIGURE 1. Study area.

neurons (similar to brain nerves) build up each layer. They are non-linear processing units. However, all of the neurons in a layer are linked together and form networks with all of the other neurons in the surrounding layers. Weighted connections between neurons in successive layers are also a feature of this method. When information passes from a neuron to the, or even from a layer to another, this is called a ''forward connection''. Network connectivity between neurons is dynamically adjusted [32] is how this spontaneous learning is performed.

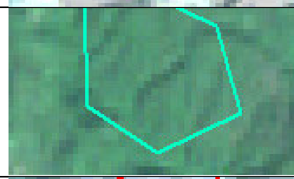
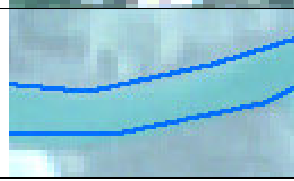
A gradient-decent method called back propagation, is one of the most essential algorithms used by ANNs. An important role is to reduce the difference between network outputs and training input/output pairs [33]. Repeated input/output pairs are sent back and forth between input and output layers, causing the error to be propagated. The weights of the backward pathways are refreshed by the learning rate and update rule [34]. ANNs cannot be uniquely identified by their default processing unit, training, or learning rate alone. This means that only a trial and error approach of changing the model parameters can yield the best results. Multilayer perceptions (MLPs) ANNs are modeled in this research utilizing the R environment v3.6.3 by using a layered feed-forward model.

Mathematically, the MLP structure may be explained. There are n_0 neurons that collect the normalized input variables x_i $(i = 1, 2\ldots\ldots\ldots n_0)$ in the MLP architecture's input layer. Second, the ''hidden layer,'' which contains the n_1 neurons and gets the first layer's output in the form of a collection of variables called $y_j (j = 1, 2\ldots\ldots\ldots n_1)$. For each layer, all neurons that correct their outputs receive a bias value of 1. The n_2 neurons in the output layer have a number of output variables $z_k (k = 1, 2\ldots\ldots\ldots n_2)$. This is known as the third or output layer. The n_0 neurons of x_i variables in the output layer are mapped to the y_i variables in the hidden

TABLE 1. Satellite data specifications.

Satellite Name	Acquisition Date	Spatial Resolution	Spectral Resolution	Purpose of Use
Sentinel-2A and Sentinel-2B	09/01/2017 and 08/01/2021	(10 m to 60 m)	13 bands	Forest monitoring and land cover changes detection
WorldView-2	25/11/2019	0.5 m	8 bands	Validation of land cover classification
Landsat-8 OLI	10/01/2017 and 05/01/2021	(30 m to 100 m)	11 bands	Earth surface temperature

TABLE 2. An outline of the identified LULC types.

LULC Type	Description	Sample Example
Agriculture	Area covered by agricultural field and salt field	
Forest	Area covered by vegetation and forest	
Settlement	Area covered by built-up and road	
Water	Area covered by river, pond and wetlands	

layer using an activation function after summarizing them using the activation function. Each hidden layer has a certain weight assigned to the neurons in that layer, which is used as a parameter of this function [35]. An example of an ANN training algorithm is the back-propagation algorithm, which is described by the minimization of the cost function in the following equation.

$$m = \frac{1}{2}\sum_{i=1}^{n} (a_i - b_i)^2 \tag{1}$$

where n is the number of classes, a_i is the anticipated output, and b_i is the response of the ANN intended to produce output from neuron I of the total n output neurons. The hyperparameters used are as follows:

Number of layers: 2
Number of neurons: [128, 256] for each layer
Learning rate: 0.001
Batch size: 32
Activation function: ReLU
Dropout rate: 0.3
Optimizer: Adam
Number of hidden layers: 1

The optimizer and learning rate were tuned accordingly. These values were determined through experimentation and tuning. Granted more layers can ever so slightly increase the accuracy of the output but as can be seen from the results the above parameters were satisfactory. We did not want to risk overfitting the data that might lead to problems in accuracy.

Figure 2 provides a visual representation of the structure of an ANN model. The model comprises input layers, which in this case represent the different spectral bands of a Sentinel satellite image. The hidden layers are sandwiched between the input and output layers, and they are responsible for learning the complex patterns and features in the input data. The output layers produce the predicted classes or labels, which in this case represent agriculture, forest, settlement, and water. The bias parameters B1 and B2 are associated with the hidden and output layers, respectively. The bias terms are constant values that are added to the weighted sum of inputs before applying an activation function. The purpose of the bias terms is to help shift the activation function to the left or right, which can help the neural network achieve a better fit to the training data. By adjusting the bias terms in the hidden and output layers, the ANN can learn to recognize more subtle patterns in the input data and produce more accurate predictions.

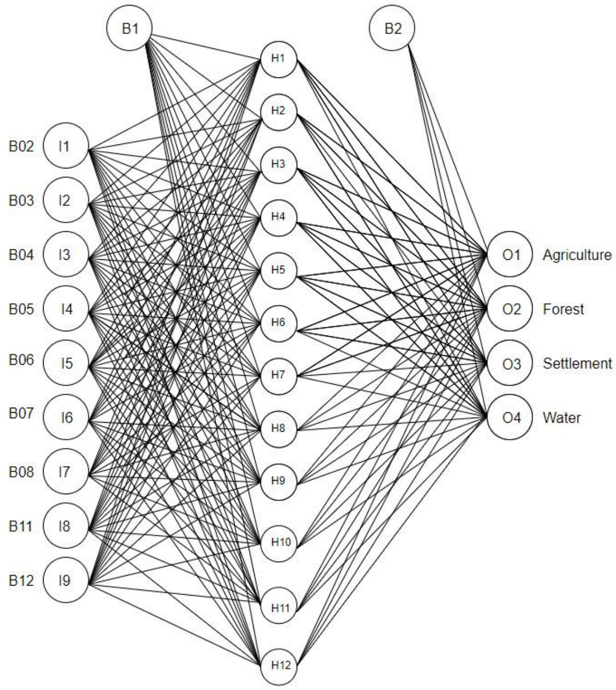


FIGURE 2. ANN model structure for LULC classification.

D. VALIDATION OF THE LULC CLASSIFICATION

ANN based LULC maps for both the pre- and post-Rohingya influx were generated, and their accuracy was measured using overall accuracy (OA) and the Kappa coefficient (K). The map's classification accuracy was evaluated/validated by constructing a confusion matrix that compares the values assigned to the reference and classified pixels. Building a map from remotely sensed data involves many steps, one of the most important and interesting of which is investigating the sources of inconsistencies found in the confusion matrix [36]. By using this confusion matrix the accuracy estimates (i.e., OA and K) were calculated using the following equation.

E. ESTIMATION OF LAND USE SPECIFIC CARBON EMISSIONS

Deforestation and degradation of forest land due to construction of Rohingya refugees' settlements are the major causes of massive carbon emissions in the study region [37]. Among variety of sources regarding carbon emission, only land use-specific carbon emissions and absorptions were considered in this study. Carbon emissions and absorptions were calculated using LULC data of two-time fames (i.e., the pre-influx period (January 2017) and the post-influx era (January 2021)). The following equation is used for estimating the land-specific carbon emissions and absorptions as suggested by Cui et al. [2].

$$LCE_i = \sum A_i \times \delta_i \times \left(\frac{M_{CO_2}}{M_c}\right) \tag{4}$$

where, LCE_i = carbon emissions and absorptions from i LULC type; A_i = Area of LULC type *I (calculated from classified LULC map)*; δ_i = carbon emissions and absorptions coefficients for *i* LULC type (coefficients applied in previous study), $M_{CO2}/M_C = Molar\ mass\ of\ CO_2/\ Atomic\ mass\ of\ C$.

For carbon emissions, the δ_i is positive; for carbon absorptions, the δ_i is negative [2]. The carbon emissions and absorptions coefficients which are validated for South Asian countries by Cui et al. [2], Fattah et al. [23], and Fang et al. [35] are shown in Table 3.

TABLE 3. The coefficient of carbon absorption and emission for different LULC types.

LULC Type	Carbon emissions and absorptions coefficient (kg(C)m^{-2}a^{-1})
Agriculture	0.0497
Forest	-0.0645
Settlement	0.0724
Water	-0.0459

F. ESTIMATION OF LST

We calculated the LST for two time-frames (i.e., 2017 and 2021) using Landsat 8 Operational Land Imager (OLI) images. The processes followed for LST estimation are in accordance with Avdan and Jovanovska [39] who used several equations to obtain several input parameters that are finally used in LST computation. Band 10 (thermal infrared (TIRS-1) is utilized in the first step of the algorithm to translate the digital numbers (DNs) into top of atmosphere (TOA) spectral radiation.

$$L_\lambda = (M_L \times Q_{CAL}) + A_V - O_i \tag{5}$$

where ML denotes the band-specific multiplicative rescaling factor, QCAL denotes the Band 10 DNs, and AL denotes the band-specific additive rescaling factor, Oi denotes the Band 10 adjustment [40].

Utilizing the thermal constants supplied in the metadata file, spectral radiance of Band 10 was converted to brightness temperature (BT) following the formula of U.S. Geological Survey [41] which is shown in the below equation.

$$BT = \frac{K_2}{\ln[\left(\frac{K_1}{L_\lambda}\right) + 1} - 273.15 \tag{6}$$

where, K_1 and K_2 = the band-specific thermal conversion constants from the metadata. The radiant temperature is recalculated by adding absolute zero to get the data in Celsius [42].

The Normalized Difference Vegetation Index (NDVI) was calculated using visible and near-infrared bands.

$$NDVI = \frac{NIR - R}{NIR + R} \tag{7}$$

where, NIR = the near-infrared band (Band 5) and R = the red band (Band 4).

NDVI was used to figure out the proportion of the vegetation (P_V) and later P_V was used to calculate the the land surface emissivity (ε_λ). The formula is presented below.

$$P_V = (\frac{NDVI - NDVI_{min}}{NDVI_{max} + NDVI_{min}})^2 \tag{8}$$

$$P_V = (0.004 \times P_V) + 0.986 \tag{9}$$

where, 0.004 = a constant value and 0.986 = the correction value for the equation

Finally, the LST was calculated using the following equation suggested by Avdan and Jovanovska [39].

$$LST = \frac{BT}{\left(1 + \frac{\lambda BT}{\rho}\right) \ln\varepsilon_\lambda} \tag{10}$$

where, λ = the wavelength of emitted radiance (10.895) and $\rho = 1.438 \times 10^{-2}$ m K.

IV. RESULTS

A. LULC DYNAMICS IN THE ROHINGYA REFUGEE INFLUX AREA

This research has investigated the effects of the influx of Rohingya refugees in the land use land cover dynamics of the study region using ANN supervised classification techniques. The results are presented in several plates of Figure 3 (a-h). The ANN classifier's kappa values for the years 2017 and 2021 were calculated to be 0.96 and 0.89, respectively. Across two time periods, kappa values correlate well with both observed and conceptualized LULC types. Images classified using an ANN had an overall accuracy of 0.97 in 2017 and 0.91 in 2021.

Figure 3 displays the LULC class distribution as determined by an ANN classifier. Multiple LULC may be seen in the study area in 2017 (i.e., before the largest Rohingya Refugee Influx in 2017). About 43.59 percentage (or 96.46 square mile) of the area under investigation was used for forestry (Table 4 and Figure 4). A total of 27.25 percent of the study area was made up of built-up regions, while 20.44 percent was used for agriculture. About 8.72% area was covered by water in the study area. Figure 4 depicts vast changes in LULCs in 2021 as compared to that in 2017. In 2017, people fleeing Rakhine state in Myanmar crossed the Naf River to Bangladesh (i.e., the western part of the study area). Rohingya refugees would rather live in the hills around their communities than on the flat land. In 2021, area under settlements increased from 27.25 (2017) to 35.49 percent. On the contrary forest land reduced from 43.59 (2017) to 34.02% in 2021. However during this period changes in water bodies and agricultural field are barely minimum.

Due to the massive influxof refugees, the forest land cover reduced by 9.58 percent, or 21.19 square mile. Many Rohingya refugees have settled in the newly-created settlements after clearing the forest lands. Some there studies have reported almost similar findings. Many natural areas, including forests and lakes, have been cleared for agricultural use. Large-scale cutting of the protected highland forest has had an adverse effect on the environment, livelihood, and biodiversity of the studied area. The area of waterbodies increases due to salt agriculture in the southern part of the study area.

B. IMPACT OF ROHINGYA REFUGEE INFLUX ON LAND-SPECIFIC CARBON EMISSIONS

The major LULC types contributing to carbon absorptions are forest and water. Similarly, agriculture and settlement are responsible for causing carbon emissions. In 2017, the amount of carbon emitted from agriculture and settlements were approximately 23525.44 tons/year and 45690.71 tons/year. Therefore total emission was 69216.15 tons/year during the same time carbon absorption were (-) 65127.96 tons/year (by forest land) and (-) 9275.22 tons/year (by water bodies). Total absorption of carbon was 74403.18 tons/year in 2017. Therefore, net carbon balance (absorption) was 5187.03 tons/year in 2017. Carbon emissions from agriculture and settlement went up to 23810.85 tons/year and 59518.63 tons/year in 2021 due to the conversion of other land use types into settlement LULC types to house this huge Rohingya refugees. Carbon absorption by forest falls to -50820.92 tons/year in 2021, although there is a small increase in carbon absorption (-10426.32 tons/year) by water. Net carbon balance (emission) in 2021 appears to be 22082.24 tons/year in 2021. Figure 5 depicts the spatial distribution of land-use-based carbon emission and absorption. According to Table 5, the net land-use based carbon emission recorded for the year 2017 is found to be negative, which means that in 2017, total absorption (74403.18 tons/year) exceeded the total emission (69216.15 tons/year) of carbon by 5187.02 tons/year. On the other hand, the net emission in 2021 was estimated at 2208.24 tons/year, with a total emission of 83329.48 tons/year and a total absorption of

$$Overall - accuracy = \frac{\text{Total pixels classified correctly pixels}}{\text{Total reference pixels}} \times 100\% \tag{2}$$

$$Kappa - coefficient = \frac{\text{Total sample num} \times Total\ corrected\ sample\ num - \sum(cal.tot \times row.tot)}{\text{Total sample num}^2 - \sum(cal.tot \times row.tot)} \times 100\% \tag{3}$$

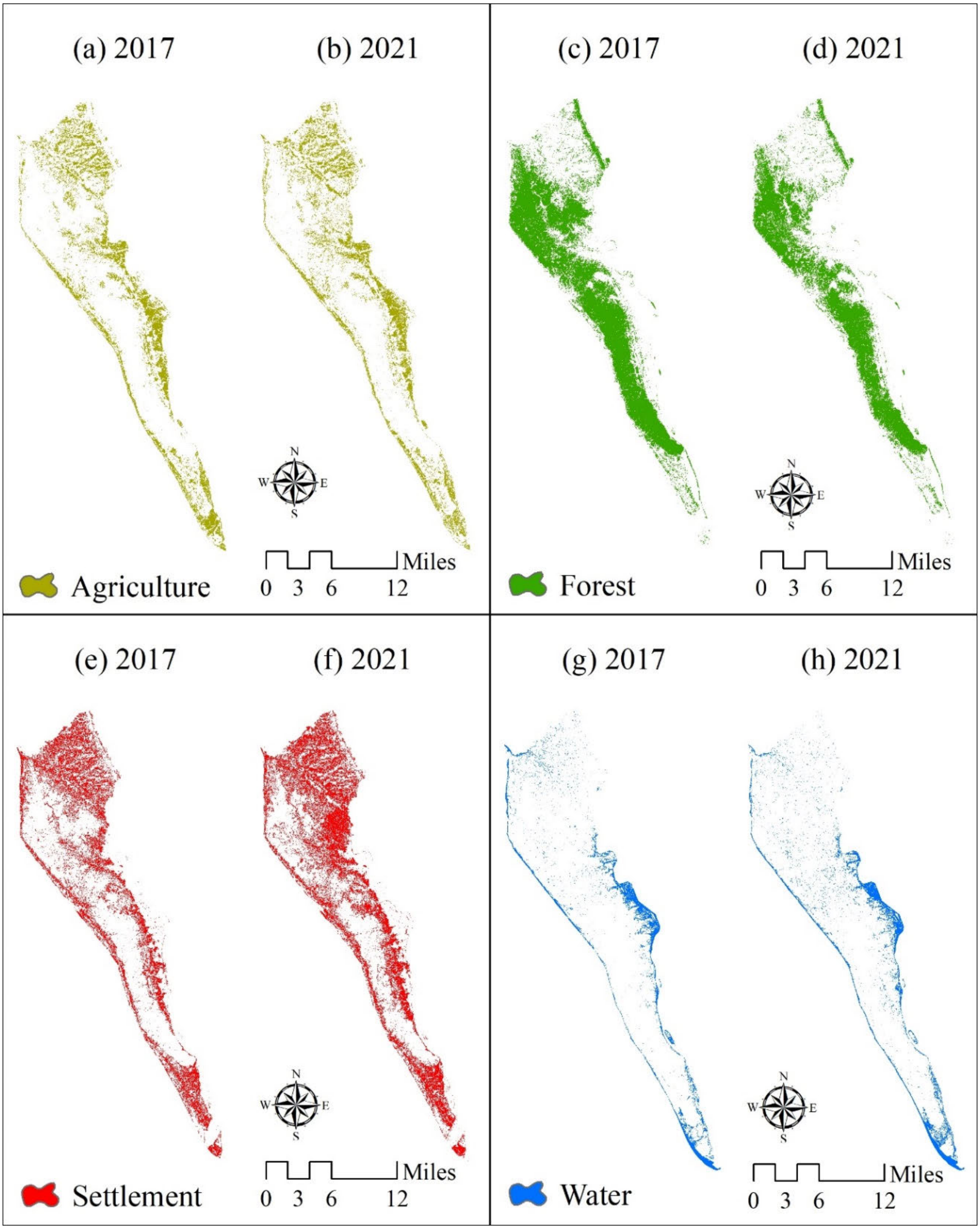


FIGURE 3. Spatial distribution of LULC type using ANN in study area.

61247.24 tons/year. Therefore, finding suggests that massive changes in land use and land cover associated with Rohingya refugees' influx has contributes to release of more carbon than earlier.

C. IMPACT OF ROHINGYA REFUGEE INFLUX ON LST

The impact of Rohingya refugee influx on land surface temperature (LST) through the change in LULC is presented in Figure 6. The Figure 6 shows the spatial distribution of LST over the study area for the years 2017 and 2021. The LSTs were classified into four categories (in °C), i.e., 18-21, 22-23, 24-25, and 26-34. LSTs were mostly found in categories 22–23 and 24–25 at the locations of Rohingya refugee camps in Ukhiya and Teknaf in 2017 (Figure 6 (a)). But in 2021, due to this influx-induced LULC alteration, the LSTs at these refugee camp sites went up to 26–34 (Figure 6 (b)). Almost

TABLE 4. Area of different LULC types in study area.

LULC Type	2017	2021	Change
	Area [square mile]	Area [square mile]	[square mile]
Agriculture	45.22	45.76	0.55
Forest	96.46	75.27	-21.19
Settlement	60.29	78.53	18.24
Water	19.31	21.70	2.39
Total	221.26	221.26	

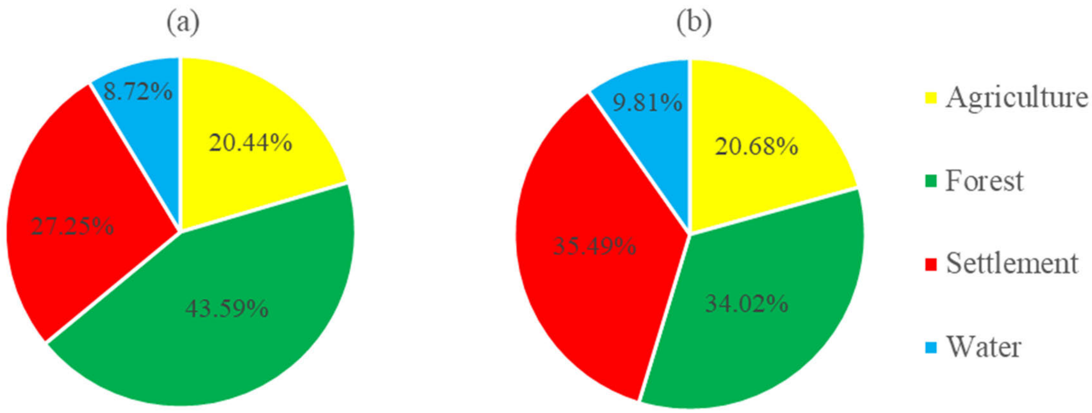


FIGURE 4. Percentage of area of LULC in Ukhiya and Teknaf Upazilas from (a) 2017 to (b) 2021.

all of the camp areas at Ukhiya fall within the LST range of 26–34, while the camps at Teknaf predominantly belong to the categories of 24–25 and 26–34. The gradual need for housing and shelter escalated the LULC alterations, converting forest lands into settlements and agricultural lands, contributing to rising LSTs in the study area as time passes. The LST of the study area for 2017 ranges from 18°C to 34°C, which has been ranged in 2021 by 19°C to 32.5°C. For both periods, the time when the images were collected, was the same. Additionally, it is to be mentioned that in 2021, strict lock-down was imposed throughout the country because of the COVID-19 pandemic. Therefore, the economic activities were almost closed. Even after that, we observed increasing temperature in the study area. The reasons should be the clearance of the forest cover in the study area and emission of gases generated from additional activities of Rohingya people.

V. DISCUSSION

This article's contribution is its extensive research of the influence of the Rohingya refugee influx on land use dynamics, carbon emissions, and land surface temperature in Bangladesh's Cox's Bazar area. The study provides quantitative insights into the changes occurring in the studied area by utilizing modern approaches such as artificial neural networks and satellite imagery. The findings have policy significance and can inform decision-making processes connected to natural resource conservation and sustainable development in regions experiencing similar refugee influxes. The study adds to the scientific understanding of the environmental implications of forced migration and emphasizes the significance of taking these aspects into account in resource management and policy formation.

First of all, an ANN has been used in order to calculate the LULC pattern in the study area. Previous studies have followed different traditional and machine learning algorithms to measure and predict the LULC pattern of Cox's Bazar [18], [43], [44], [45]. ANN is found to be more accurate in terms of providing results compared to other types of algorithms for measuring LULC [10], [43], [46], [47], [48]. From Figure 4, it can be seen that settlements increased from 27.45% to 35.49% and forests decreased from 43.9% to 34.02%, which creates an ideal situation for the increase in carbon emissions. Biasness was moderate in some extents in the neurons of ANN, and it ran several times to clear it, and the overall weight is 274. The kappa values for the ANN classifier in 2017 were 0.96, and in 2021 they were 0.89. The kappa values correspond positively with both empirically seen and theoretically predicted forms of LULC throughout the two time periods. In 2017, an ANN's overall accuracy for image classification was 0.97, and by 2021, it had dropped to 0.91.

From the findings (Table 6) a clear linkage among Rohingya refugee influx (and settlement), land use transformation, Carbon emission and LST has surfaced. Among

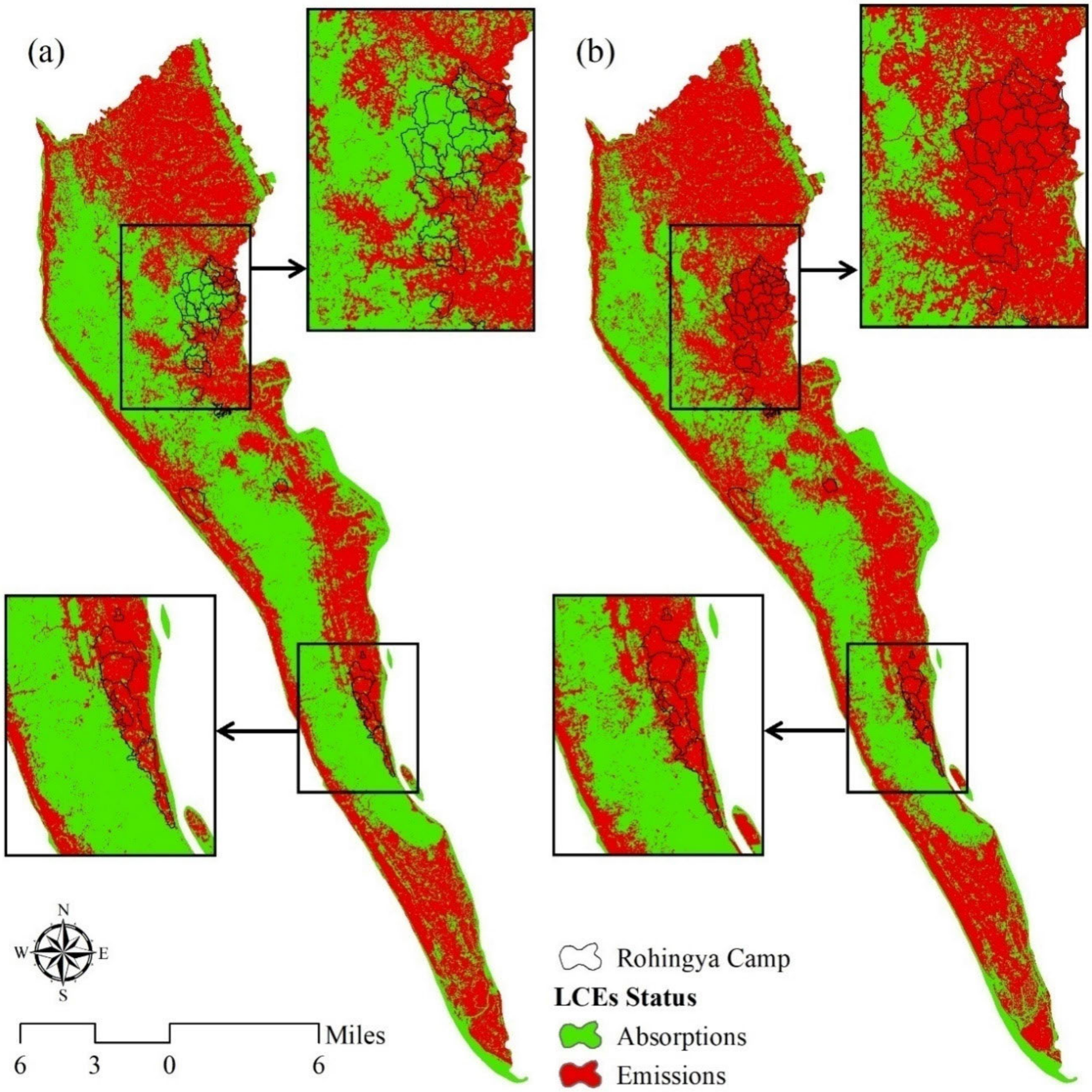


FIGURE 5. Spatial distribution of land-use based carbon emission and absorption in the study area (a) in 2017; (b) in 2021.

TABLE 5. Statistics on carbon emissions and absorption based on land use in the study area.

LULC type	Land-use based carbon emission and absorption (tons/year)	
	2017	2021
Agriculture	23525.44	23810.85
Forest	-65127.96	-50820.92
Settlement	45690.71	59518.63
Water	-9275.22	-10426.32
Total emissions	69216.15	83329.48
Total absorptions	-74403.18	-61247.24
Net emission	-5187.02	22082.24

the entire study region of Cox's Bazar, the area capable of absorbing carbon reduced from 46.94 square mile to 34.95 square mile in Ukhiya Upazila alone after the influx of Rohingyua refugees. On the contrary, in the same period area having potential for carbon emission has been increased from 53.13 square miles to 65.12 square miles. In Teknaf Upazila, the area capable of absorbing carbon reduced from 68.56 square mile to 61.74 square mile after the influx of

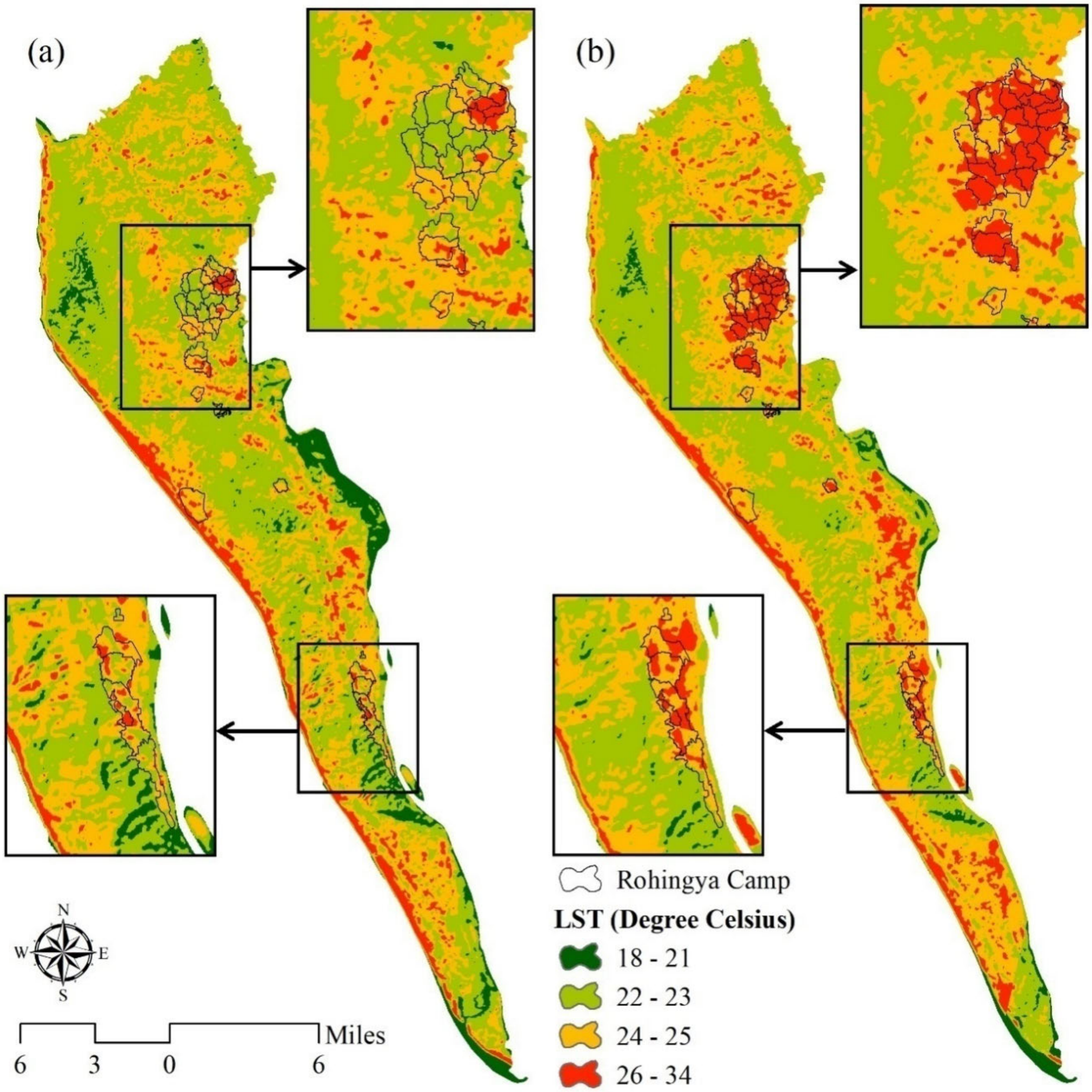


FIGURE 6. Spatial distribution of LST in study area (a) in 2017; (b) in 2021.

Rohingya refugees. On the contrary, in Teknaf in the same period, the area having potential for carbon emission has been increased from 52.6 square miles to 59.42 square miles. In Ukhiya 14.64% carbon absorption area has been reduced while 10.14% carbon emission area increased. It means net carbon emission increased from 24.78% area in Ukhiya. In Teknaf Upazila, 6.82% carbon absorption area has been reduced while 6.09% carbon emission area increased. Therefore, net carbon emission increased from 12.91% area in Tekhnaf. (Table 6). Moreover, careful scrutiny shows that, the refugee camp areas/sites in these upazilas have triggered significant change in carbon concentration and temperature build up in localized scale between 2017 and 2021. The Rohingya refugee camp sites in Ukhiya as well as Teknaf exhibited 93.24% and 29.43% reduction in carbon absorption's area in addition to 45.61% and 5.99% growth in carbon emission areas respectively.

The changes in temperature in the refugee camp areas/sites are found significantly higher than the rest of the areas of Ukhiya and Teknaf. The decline in carbon absorption areas has contributed to 1.48^0C (1.62%) and 0.74^0C (.66%) increase in mean temperature in the Rohingya refugee camp sites in Ukhiya and Teknaf Upazila respectively. In fact, in all the campsites the forest lands are converted to refugee shelters having roofs of corrugated iron sheets which further contribute to temperature increase and change in microclimate.

These key findings have several policy and strategic implications that demand immediate attention. Ukhiya and Teknaf Upazilas of Cox's Bazar district- the key tourist destination of Bangladesh, hosted the majority of Rohingya refugees who had entered Bangladesh due to the political violence in Myanmar. Sudden influx of refugees was so high that from humanitarian ground the hospitable local people make

TABLE 6. Relation among rohingya refugee influx, land use specific CEs and LST.

	Land Use Specific Carbon		2017	2021	Changes
UkhiyaUpazila	Absorptions	Area (Square Miles)	46.94	34.95	-11.99
		Percentage	57.32	42.68	-14.64
		Mean Temperature (^{0}C)	22.36	22.34	-0.02
	Emissions	Area (Square Miles)	53.13	65.12	11.99
		Percentage	44.93	55.07	10.14
		Mean Temperature (^{0}C)	23.45	23.84	0.39
TeknafUpazila	Absorptions	Area (Square Miles)	68.56	61.74	-6.82
		Percentage	52.62	47.38	-5.23
		Mean Temperature (^{0}C)	22.26	22.43	0.17
	Emissions	Area (Square Miles)	52.6	59.42	6.82
		Percentage	46.95	53.05	6.09
		Mean Temperature (^{0}C)	23.81	24.06	0.26
Rohingya Refugee Camps in Ukhiya	Absorptions	Area (Square Miles)	4.27	0.15	-4.12
		Percentage	96.62	3.38	-93.24
		Mean Temperature (^{0}C)	23.02	24.5	1.48
	Emissions	Area (Square Miles)	2.46	6.58	4.12
		Percentage	27.2	72.8	45.61
		Mean Temperature (^{0}C)	24.34	25.96	1.62
Rohingya Refugee Camps in Teknaf	Absorptions	Area (Square Miles)	0.79	0.43	-0.36
		Percentage	64.71	35.29	-29.43
		Mean Temperature (^{0}C)	22.89	23.62	0.74
	Emissions	Area (Square Miles)	2.81	3.16	0.36
		Percentage	47	53	5.99
		Mean Temperature (^{0}C)	24	24.66	0.66

room to accommodate them before the government administration and other stakeholders appeared in the scene. As a consequence, in the two Upazilas, there were more refugees than locals, with some estimates putting the ratio at three refugees for every local/native person. At a point in time the density of population in Rohingya refugee camp site goes as high as 60 thousand person per square kilometer. It is believed that due to unplanned construction and expansion of camp sites by disregarding the local ecology and ecosystem the carrying capacity of local environmental has been severely compromised which has been reported in many earlier studies. Our findings are in conformity with many others who have identified that apart from construction of human settlements for refugees' roads, stairwells, water retention small ponds, are built by clearing forest land and cutting of hill slopes. Needless to say all have an adverse effect on the local and forests environment. The influx of Rohingya has altered the forest environment as a whole. There is a detrimental impact on natural beauty and wildlife preserves. Many trees were cut down for fuel and construction, destroying the ecological benefits that woods provide. It is advised that the impact of the inflow of Rohingya refugees on the environment and society be closely monitored. As a result, remote sensing data were used in this research to determine how the inflow of Rohingya refugees has affected CEs pattern and LST dynamics. High-quality LULC maps at both times, before and after the Rohingya refugee surge, were created as the primary input for this research. To accomplish LULC mapping, ANN algorithm was used. The ANN showed higher accuracy and used to estimate land use based CEs pattern for the years 2017 and 2021. The changes of LST were also estimated for 2017 (i.e., before Rohingya refugee influx) and 2021. The massive influx of Rohingya refugees in 2017 has an intense effect on the LULC of Ukhiya and Teknaf uazilas. Thousands of Rohingya have been coerced into migrating to Bangladesh since the 1970s, and the government there has always welcomed them. In 2017, 96.46 square mile (43.59%) of the LULC in the research area was consisted of hilly forest land. Rohingya refugees had settled in highland forests due to the higher concentration of public resources there. Rohingya refugees had clustered in areas where trees and hills were removed. In the absence of a control group, the LULC type had been altered by the provision of temporary housing in mountainous forest regions for a large influx of migrants. The refugee camps caused a decline of forests by 9.58 percent (i.e., 21.19 square mile) and an increase of settlements by 8.25 percent (i.e., 18.24 square mile). A growing number of Rohingya homes reportedly were in need of fuel wood or timber, which is sourced from nearby forests. As of now, 750,000 kg of fuel wood is needed daily by Rohingya families [49], putting a massive strain on the region's already stressed forest resources. A growing body of research indicates that migrants have already removed forest land in Rohingya Refugee Influx Area [16], [50], [51]. The massive inflow of Rohingya refugees caused an increase in carbon emissions in the Ukhiya and Teknaf upazilas. In 2017, total absorption (74403.18 tons/year) was higher than total emission (69216.15 tons/year) of carbon, yielding a negative net land-use based carbon emission of −5187.02 tons/year. However, it was estimated that in 2021 the net emission would be 2208.24 tons/year, with a total of 83329.48 tons/year being emitted and 61247.24 tons/year being absorbed. Increasing carbon emissions have led to rise in LST. The decrease in absorptions and the rise in emissions have each led to a 1.48°C and 0.74°C increase in mean temperature in the Rohingya refugee camps in Ukhiya and Teknaf, respectively. Increasing LSTs in the study region may be attributed, in part, to the progressive increase in the need for housing and shelter, which in turn led to the LULC changes that converted forest areas into settlements and agricultural fields. As previous studies reported, the LST in Rohingya refugee influx area and the adjacent region has risen by 1.3 degrees Celsius between 2017 and 2019 [17].

VI. CONCLUSION

Examining the effect of the Rohingya refugee influx on the CEs pattern and LST dynamics in the Ukhiya and Teknaf upazilas of Cox's bazar district, this study considered a variety of methods for showcasing the differences in LULC, land use specific CEs, and LST before and after the influx. In order to determine how the inflow of Rohingya migrants has affected LULC, ANN supervised machine learning method is used. It was determined that between 2017 and 2021, a decline of forests by 21.19 square mile (9.58 percent) and an increase of settlements by 18.24 square mile (8.25 percent) had been occurred. In 2017, a negative net land-use based carbon emission of −5187.02 tons/year was observed. In 2021, it was predicted that annual net emissions will total 2208.24 tons. Increasing carbon emissions have led to rise in LST of the study period.

However, a major barrier to accurately showing forest cover changes was the lack of cloud-free satellite data, despite the fact that this study has several applications (such as forest conservation and policy). Subsequent studies may make advantage of hyper-spectral image data gathered during the monsoon season to determine the mechanisms that govern shrub and mixed forest growth in the area. Despite these caveats, the geographical data collected in this research played a very useful role in assessing how the refugee situation in Bangladesh has affected the natural world.

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