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Research article

# Spatio-temporal variation of land use and land cover changes and their impact on land surface temperature: A case of Kutupalong Refugee Camp, Bangladesh

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## HIGHLIGHTS

- Kutupalong Refugee Camp area is undergoing a rapid LULC change process.
- A dramatic increase in built-up land and deforestation is observed from the year 2015–2021.
- Land Surface Temperature is increasing rapidly in the campsites.

## ARTICLE INFO

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## ABSTRACT

Environmental degradation can be predicted and managed in a sustainable manner by the perodic analysis of the Land Use/Land Cover (LULC) change pattern, which not only helps to revitalize the environment but also helps to improve future land-use policies. With the Rohingya influx in 2017, the Kutupalong Mega Camp area in Bangladesh is at a severe risk of environmental degradation as the area is experiencing remarkable LULC change. The aim of this research is to illustrate the LULC change in the Kutupalong Mega Camp before and after the refugee influx, as well as its impact on the surrounding environment because of this change. The spatial and temporal variation of the LULC is analyzed from the classified multi-temporal Landsat images for years-2015, 2018, and 2021. The study reveals gradual decrease in forest cover of the area, which is replaced by the increasing human settlements. The study found an inverse relation between the refugee influx and the vegetation cover, where a positive relation to the bare land and settlement exists. The area experienced about ten times increase in human settlements during 2015–2021, which resulted deforestation of surrounding forest cover. Between 2015 to 2021, 74 % of forest cover of the studied area has been cleaned up for newer settlements, with an increase of wetland to meet the needs of increasing refugee population which has made the scenario worse. We also noticed an increase of Land Surface Temperature (LST) within a short period, where the average temperature increase rate is 0.06% during 2015–2018 and 0.01% during 2018–2021. The ecosystem, wild-habitat, and the thermal environment has been disturbed to a great extent due to this drastic change of forest cover mostly by the increasing anthropogenic activities in this area. The study represents the present scenario in comparison to its natural setting just a few years ago, and may serve as a guidance for the concerned authorities and international humanitarian organizations to develop a sustainable, comprehensive, and environment-friendly land management plan in order to protect the surrounding forest-ecology as well as the humanitarian works.

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## 1. Introduction

Detection of land use and land cover changes pattern is a well-known method to assess environmental and ecological degradation (Beevi et al., 2015; Hadeel et al., 2011). A Comprehensive study on the LULC changing pattern may ensure proper planning for natural resources and land use management. By integrating Geographic Information Science (GIS) and Remote Sensing (RS) techniques, such LULC pattern analysis can be accomplished easily and visualize the affected areas and their impacts on the surrounding environment. Several studies were conducted on LULC changes (Mondal et al., 2021, 2022; Thakur et al., 2020; Thakur et al., 2020, 2020) using various satellite data including Landsat, MODIS, and SPOT, however, Landsat satellite data has more potentiality in terms of LULC change detection studies because of free access of data with moderate spatial resolution and availability of multi-temporal time-series data from the year 1972 (Lu et al., 2019). It is intelligible that the analysis of LULC change dynamics evaluates the numerous changes in the surrounding environment of an area and help to develop an effective management plan which can assist in achieving sustainable development and appease both local and global environmental changes (Mondal & Bandyopadhyay, 2016, 2022; Chamling and Bera, 2020; Lai, 2020; Mondal et al., 2019; Mondal et al., 2016).

After the influx of the Rohingya refugees in Ukhiya, the forest, water, and land systems are being degraded rapidly due to overwhelming pressure on natural resources and other anthropogenic factors. Accommodation of the Rohingya refugees and their growing population is a major factor of the dramatic local environment and ecological change as more forest cover areas are being wiped out for building houses for them (Hossain and Moniruzzaman, 2021). Moreover, illegal logging is a common phenomenon nowadays to meet the demand for wood as fuel for both the native and refugees. These anthropogenic activities are not only ruining the local forest cover and unbalancing the ecological balance but also clear-cutting sizable areas of hills-track in order to build infrastructures which are mostly new settlements (Hassan et al., 2018). Additionally, soil erosion is becoming a common phenomenon due to the construction of shelters on denuded hills where it hampered the stream flows and reduced stream capacity to drain out excess rainwater in the monsoon period causing flash floods, and landslides thus damage of assets (Quader et al., 2020). The forest in this region is continuously decreasing in terms of quality and integrity due to global deforestation trends combined with significant anthropogenic stresses from the Rohingya population (Hossain and Moniruzzaman, 2021). The process of relocating refugees appears to be lengthy and complicated (Rashid, 2020), but forest ecosystem integrity must be conserved to prevent further damage. Therefore, the degree of stress, level of impacts, and pattern of deforestation is critical data for the forest conservation and protection process (Hasan et al., 2020) and periodic assessment of LULC changes is essential to understand the extent of human intervention in the natural settings and find out the remedy to mitigate the potential impacts of unbalanced human-environment interactions.

Several methods have been developed to detect changes in LULC such as post-classification comparison, conventional image differentiation, and manual on-screen digitization of changes (Lu et al., 2004; Reis, 2008). The post-classification comparison is a widely used technique due to the availability of multi-temporal satellite data and easy implementation of change detection comparison (pixel by pixel) by GIS and RS software. In this study, multi-temporal Landsat imageries were collected from the United States Geological Survey (USGS) website and GIS data of Kutupalong Mega Camp was collected from Humanitarian Data Exchange. All downloaded images were preprocessed and classified by the maximum likelihood classification method and post-classification image comparison was performed subsequently to detect LULC changes. Additionally, this study also presents the impact of LULC changes on the surrounding thermal environment in the Kutupalong Rohingya refugee camp.

## 2. Literature review

Geographically, Ukhia is a sub-district of Cox's Bazar in Bangladesh, with a substantial forest cover and natural habitat. However, recent overwhelming human activities (e.g. large refugee camps, illegal logging, and climate change) have drastically changed the local environment and ecosystem (Hossain and Moniruzzaman, 2021). Although the region was historically rich in forest cover where 50% of the total area was covered by vegetation, it witnessed a great change of land cover in the last 20 years and about 13% of that forest cover has been converted into other land uses (Hossain and Moniruzzaman, 2021). The rohingya settlements or the refugee camps itself is covering about 2.68% of that changed area, besides the agricultural land of this region has been occupied by the cams as well which is about 1.01% of the total agricultural land of Cox's Bazar (Hossain and Moniruzzaman, 2021). The occupancy of the refugee settlements in terms of area coverage has significantly increased between 2016 to 2017 and which increased to 1356 ha from 146 ha causing a huge deforestation (Hassan et al., 2018). This increased settlement has created a negative impact on the surrounding forest cover within a 10 km radius, and resulted in a loss of 2060 ha of forest land which is cumulatively about 18% of the surrounding forest cover of the camps. The Rohingya people are one of the world's most vulnerable and oppressed minorities, who have been forced to escape from Myanmar and seek refuge in Bangladesh (Rohingya, 2018; Hassan et al., 2018). Being concerned for the people seeking refuge and arranging a site quickly, the forest and natural resources were neglected which resulted in severe consequences for the host environment. The existing overwhelming consumption of natural resources combined with newly arriving refugee's cumulative pressures in terms of unplanned construction and land management put further strain on forest resources, accelerating deforestation and land degradation (KC & Nagata, 2006). A growing population, environmental exploitation, deforestation, incorrect land use, and human interventions are all contributing to a serious problem for the local environment and spoiling the existing human-environment relationship (Benzer, 2010).

The migration of Rohingyas into the area has exacerbated land cover fragmentation (UNDP & UN WOMEN, 2018), which has resulted in degradation of ecosystem, and services such as biomass depletion (Hasan et al., 2021). Acknowledging the LULC change pattern is important for assessing potential impacts on the local environment and ecosystems, which can assist planners, ecologists, administrators, and policymakers in managing, and formulating sustainable plans to overcome negative effects on the environment and ecosystem along with the developmen activities (Islam et al., 2007; Islam et al., 2021; Islam et al., 2021, 2021).

After the influx of Rohingyas, very little work has been conducted to examine the past and current situation in terms of land use degradation around the refugee camps, as well as the impact on the environment. Hassan et al. (2018) analyzed two Sentinel-2 imagery from December 2016 to December 2017 and found that the refugee camps occupancy rate is increasing rapidly. Between 2017 and 2018 over 8498.40 ha of vegetation covers and 687.97 ha of agricultural land converted to the built-up area (Rahman et al., 2019). Hasan et al. (2021) focused on determining how LST varies with respect to vegetation change and stated that aside from forest lands, ground biomass and carbon stock suffered significant losses throughout the study period. Also, most of the studies focused on vegetation change over the year due to the Rohingya crisis, however they neglected the impact of rapid expansion of human settlement and its impact on the surrounding thermal environment (Islam et al., 2019; Islam et al., 2022a,b). Where they ignored the spatio-temporal changes in the environment and ecosystem and its impact on the surrounding thermal environment in the Kutupalong Mega Camp area.

Table 1. The area of the 26 camps of the Kutupalong Mega Camp.

| No. | Name | Area (km$^2$) | Name | Area (km$^2$) | Total (km$^2$) |
|---|---|---|---|---|---|
| 1. | Camp 16 | 0.528398 | Camp 2W | 0.391861 | **16.9598** |
| 2. | Camp 2E | 0.390853 | Camp 11 | 0.466019 | |
| 3. | Camp 15 | 0.984412 | Camp 12 | 0.631138 | |
| 4. | Kutupalong RC | 0.387319 | Camp 1E | 0.633583 | |
| 5. | Camp 9 | 0.649084 | Camp 13 | 0.753767 | |
| 6. | Camp 10 | 0.496145 | Camp 17 | 0.954136 | |
| 7. | Camp 18 | 0.751677 | Camp 20 | 0.489106 | |
| 8. | Camp 8W | 0.772153 | Camp 8E | 0.956588 | |
| 9. | Camp 3 | 0.453561 | Camp 4 Extension | 0.497475 | |
| 10. | Camp 5 | 0.615297 | Camp 4 | 1.15514 | |
| 11. | Camp 1W | 0.534394 | Camp 20 Extension | 0.766108 | |
| 12. | Camp 6 | 0.361088 | Camp 19 | 0.769599 | |
| 13. | Camp 14 | 0.856841 | Camp 7 | 0.714086 | |

## 3. Material and methods

### 3.1. Study area

The study area (Ukhiya) is a southeastern territory of Bangladesh, which lies in Cox's Bazar district and sharing the borderline with Myanmar. Its geographic location is in between Latitude 21°12′36.70″ N to Longitude 92°9′2.41″E, with a 23-meter of average elevation in the buffer zone. The study area namely the Kutupalong Mega Camp comprised of 26 individual camps covering an area of 4190 acres (16.96 sq. km) (Table 1), where the surrounding area is about 64,056 acres (259.22 sq. km). Currently, about 919,000 Rohingya refugees residing in the Kutupalong and Nayapara refugee camps where the number of refugee people living in Kutupalong was 18,223, 200,000 and 890,000 during 2015, 2018, and 2021 respectively (UNHCR, 2022). This area characterizes diverse physiography such as undulating hillocks, piedmont plains, tidal floodplains, and a continuous line of sandy beaches that extends to Cox's Bazar along the Bay of Bengal (120 km) (Figure 2). Additionally, this area is a geographically tropical monsoon zone for its heavy rainfall (average annual rainfall is 4000 mm) with the most rain occurring in July (1029 mm), and the least rain occurring in January (2 mm). The average annual temperature is 26.1 °C where the warmest month is May (32.2°) and the coolest month is January (14.9 °C). The map of the study area has shown in Figure 1 below.

### 3.2. Data collection

This study uses both primary and secondary data for analysis where primary data was collected from the field observation as well as local people's perceptions for cross-checking ground truth data with satellite images. Moreover, Multi-spectral satellite imagery from three different years (2015, 2018, and 2021) was downloaded from the United States Geological Survey (USGS) as the secondary source to detect the changes in LULC. Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) is freely available since 2008 which provides 30 m resolution multispectral satellite data with nine different spectral bands that can be used for land cover classification. A couple of field visits was conducted to collect ground truth data to analyze the accuracy assessment of supervised classification of the satellite images.

To observe LULC changes before and after the influx of the Rohingya Refugees, Landsat images (L2 product) of different years (2015, 2018, and 2021) were collected from the United States Geological Survey (USGS) website (Table 2). The L2 image products are radiometrically corrected and preprocessed by USGS.

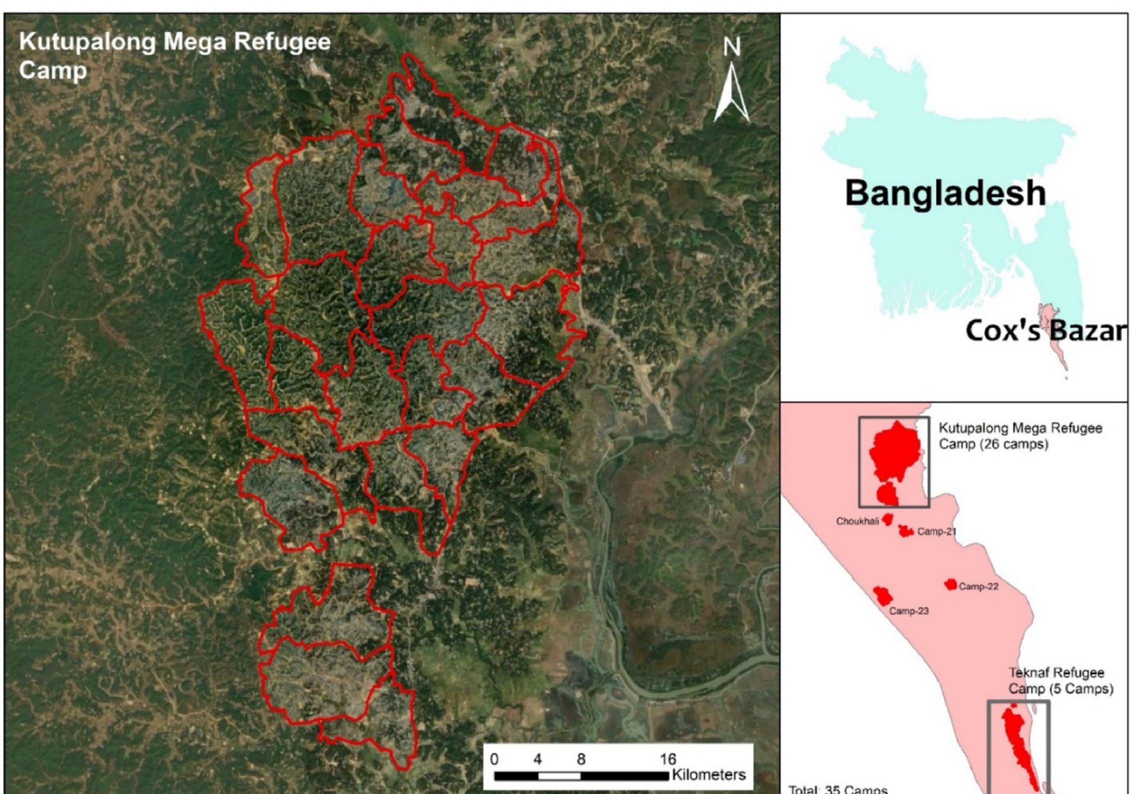


Figure 1. Location map of kutupalong mega refugee camp, Cox's bazar, Bangladesh.

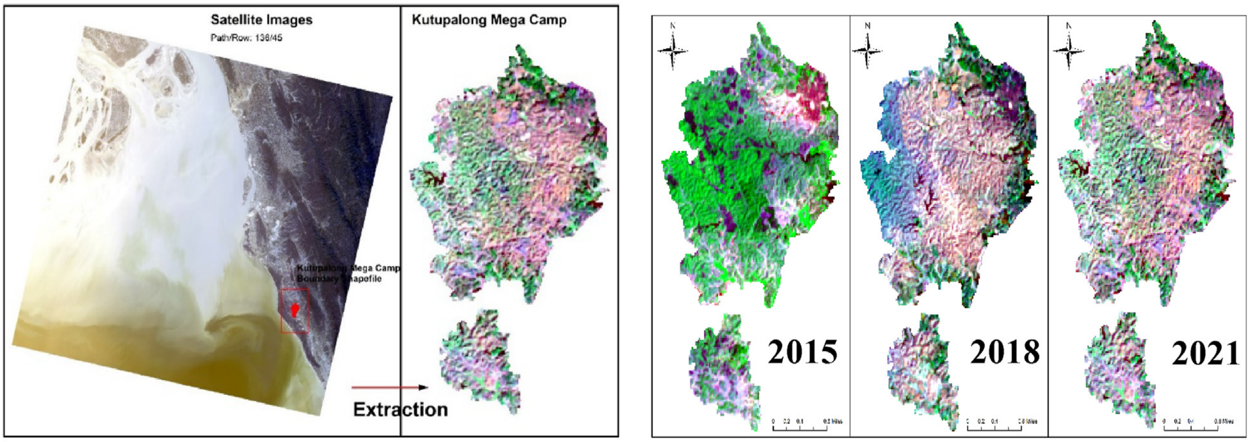


**Figure 2.** Thematic images of kutupalong mega camp.

**Table 2.** Satellite image information.

| Sensor | Path/row | Acquisition date |
| --- | --- | --- |
| Landsat 8 OLI/TIRS Operational Land Imager/Thermal Infrared Sensor | 136/45 | 19-March-2015 |
| | | 14-February-2018 |
| | | 05-January-2021 |

The area of interest (Rohingya refugee camp) was extracted from the downloaded images of different years and reprojected into Universal Transverse Mercator (UTM) WGS84, Zone 46N. The change detection technique has been adopted with the mixing of a number of ways in which multispectral satellite images from several years were processed separately and compared. The entire process has been drawn in a flow diagram (Figure 3).

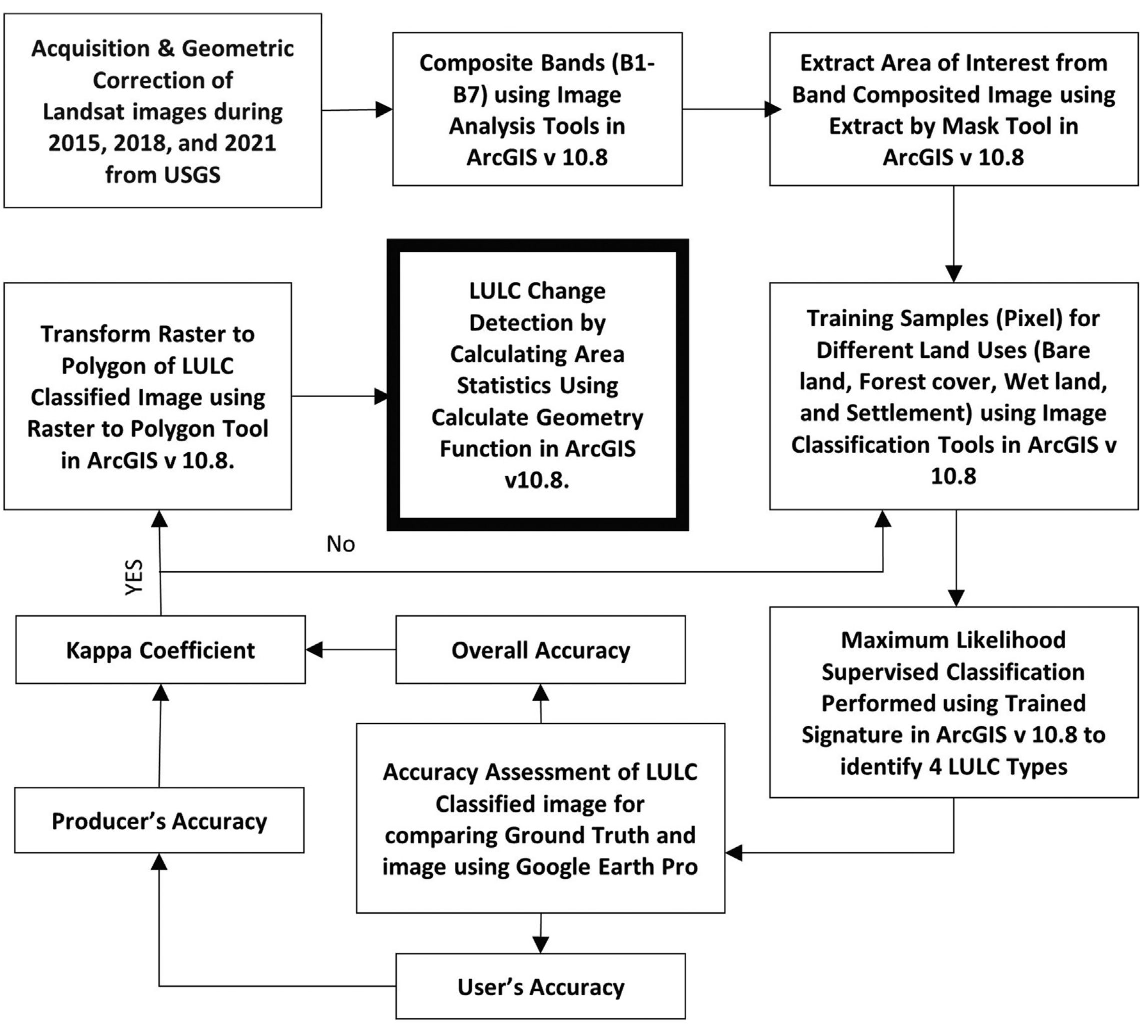


**Figure 3.** Lulc classification and change detection process.

**Table 3.** Detail classification scheme.

| Land use/land cover types | Details and Color tone |
|---|---|
| Settlement | All Infrastructure (Purple tone) |
| Forest Cover | Vegetated and Agriculture area (Red tone) |
| Bare lands | Open and fallow space (Brown tone) |
| Wetlands | Waterbodies (Blue tone) |

### 3.3. Image classification

Multi-spectral Raster images contain several bands (Landsat 8 OLI/TIRS has nine bands) that have been used for the task of digging out pixel information on every land-use class (Bare land, Forest Cover, Settlement, and Wetland). A detailed Classification scheme has been provided in the following Table 3.

The supervised maximum likelihood classification (MLC) method was applied to classify images into the four LULC classes. In the supervised maximum likelihood classification, pixels must be trained based on their color tone according to the land use classes (Settlement, Bare land, Forest Cover, and Wetland) which have been collected from the observation of ground truth value through google earth and field observation. The entire classification process was implemented in ArcGIS software (Version 10.8).

### 3.4. Accuracy assessment

Because of the uneven distribution of spectral values and spectral similarities among different classes (e.g. agricultural land – forest cover), many pixels might be misclassified in the maximum likelihood supervised classification. Accuracy assessment plays an important role in referencing the raw satellite images' pixel and ground truth value. Fifty-two random points have been created using the "Create Random Points" tool in ArcGIS v10.8 within each classified image boundary in order to compare the reference points and classified images. These created random points have been checked with the ground value using Google Earth Pro and filed observation. Later, accuracy of the classification was generated in terms of user accuracy, producer accuracy, overall accuracy, and kappa statistics. Overall accuracy has been calculated from the confusion matrix (the error matrix Table 4) by dividing the sum of the corrected samples by the sum of total samples using Eq. (1).

**Table 4.** Accuracy assessment of supervised classification.

| Land use Classes | 2015 | | 2018 | | 2021 | |
|---|---|---|---|---|---|---|
| | User Accuracy | Producer Accuracy | User Accuracy | Producer Accuracy | User Accuracy | Producer Accuracy |
| Bare land | 100% | 62% | 88% | 83% | 88% | 70% |
| Forest Cover | 94% | 100% | 100% | 85% | 88% | 88% |
| Settlement | 80% | 100% | 81% | 89% | 88% | 96% |
| Wet land | 33% | 100% | 67% | 100% | 100% | 100% |
| Overall Accuracy | 90% | | 87% | | 88% | |
| Kappa Coefficient | 81% | | 80% | | 83% | |

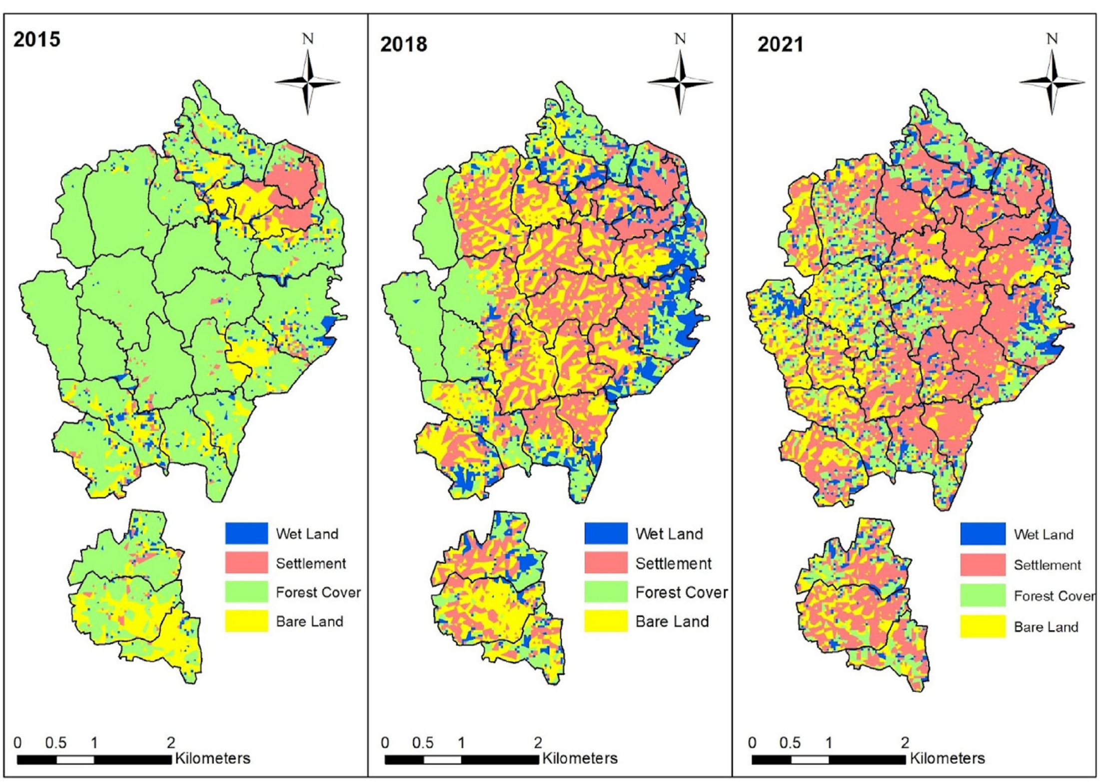


**Figure 4.** Classified mages of Kutupalong Mega Camp.

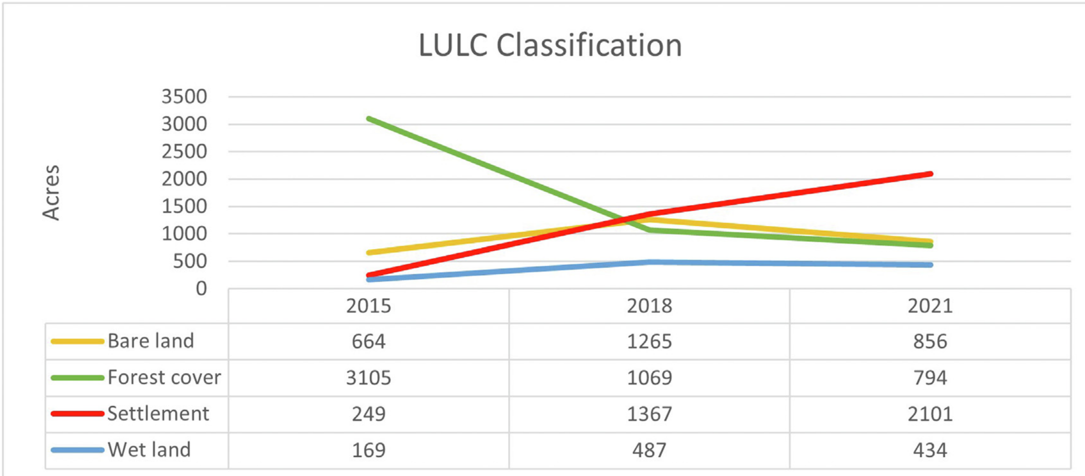


**Figure 5.** Area of LULC classes of year-2015, 2018, and 2021.

$$Overall\ Accuracy = \frac{Total\ Number\ of\ Correcttly\ Classified\ Pixels\ (Diagonal)}{Total\ Number\ of\ Reference\ Pixels} \times 100 \tag{1}$$

Kappa coefficient is calculated by using the following Eq. (2).

$$Kappa\ Coefficient\ (T) = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r}(X_{i+1} \times X_{+i})}{N^2 - \sum_{i=1}^{r}(X_{i+1} \times X_{+i})} \tag{2}$$

Where, r = represents number of rows, $X_{ii}$ = represents number of observations in row $i$ and column I.

$X_{+i}$ and $X_{i+1}$ are the marginal totals of row i and column I, respectively, N = total number of observations. The following Table 4 shows the overall accuracy as well as the kappa coefficient for the years 2015, 2018, and 2021.

## 4. Results & discussion

Changes in classified images have been detected using a supervised classification based on four different land cover types (Figure 4). In terms of land development, the rate of settlement expansion has been increasing drastically since the influx of Rohingya refugees. We found that settlement increased 10 times (from 101.8 ha to 850.24 ha) from the year 2015–2021, which has impacted all environmental components in the surrounding campsite. It is obvious that the influx of Rohingya refugees causes a dramatic change in the local environment and ecosystem.

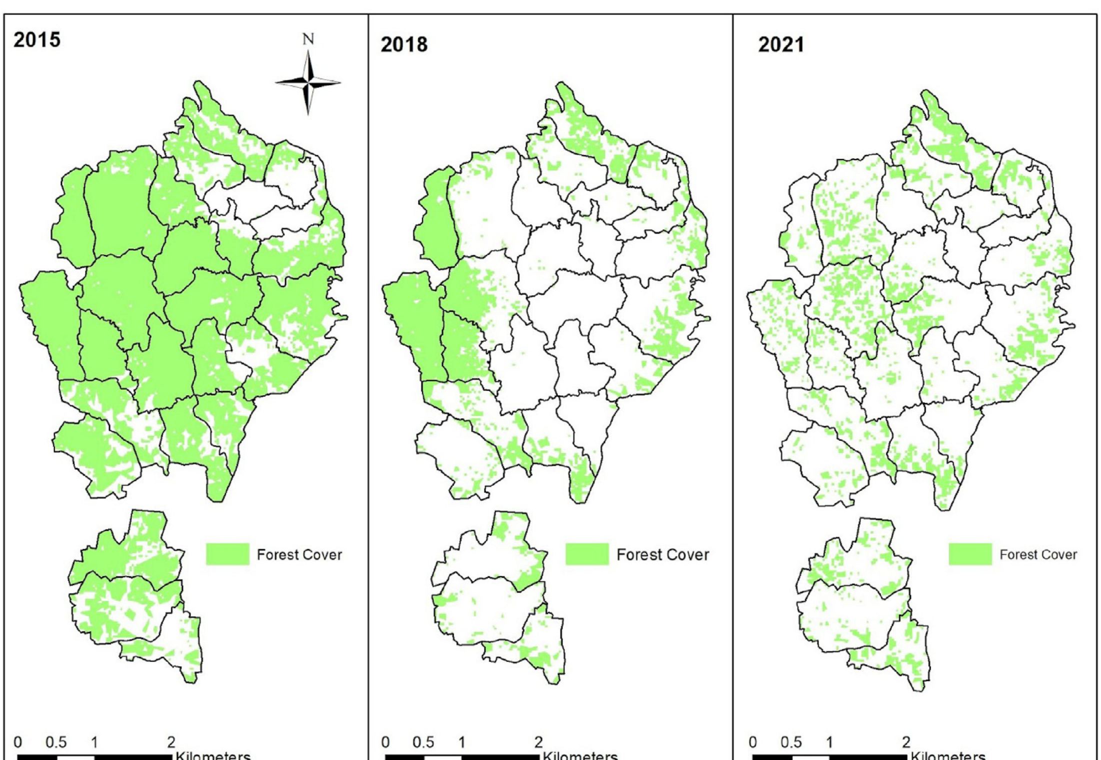


**Figure 6.** Spatio-temporal Variation of forest cover.

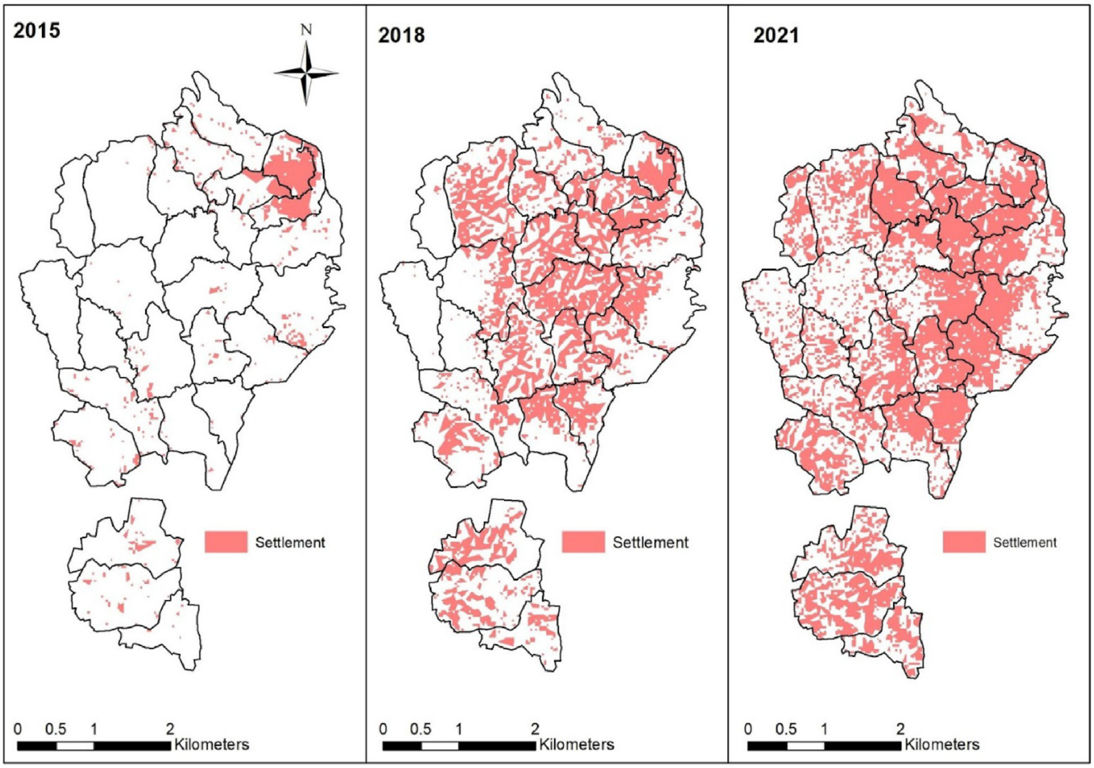


**Figure 7.** Spatio-temporal variation of settlement.

The following graph (Figure 5) also illustrates how the settlement evolves over the years after the refugee influx.

On the other hand, the Forest cover change has an inverse relation with the settlement change. It has been shrinking dramatically after the influx of Rohingya refugees. The following graph (Figure 5) also shows the rate of forest cover change in the study area. Though the bare land class was increased until 2018, it reduced slightly from 2018 to 2021. Initially, the Rohingya refugee cut down a vast amount of surrounding

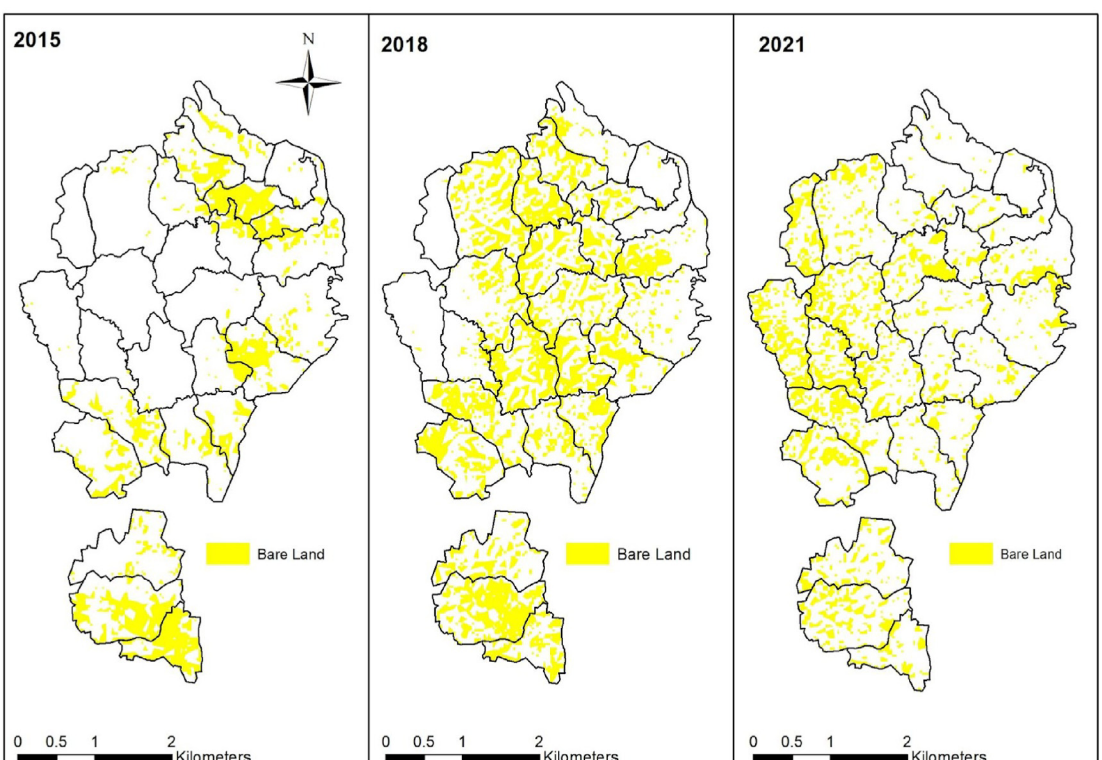


**Figure 8.** Spatio-temporal Variation of Bare land.

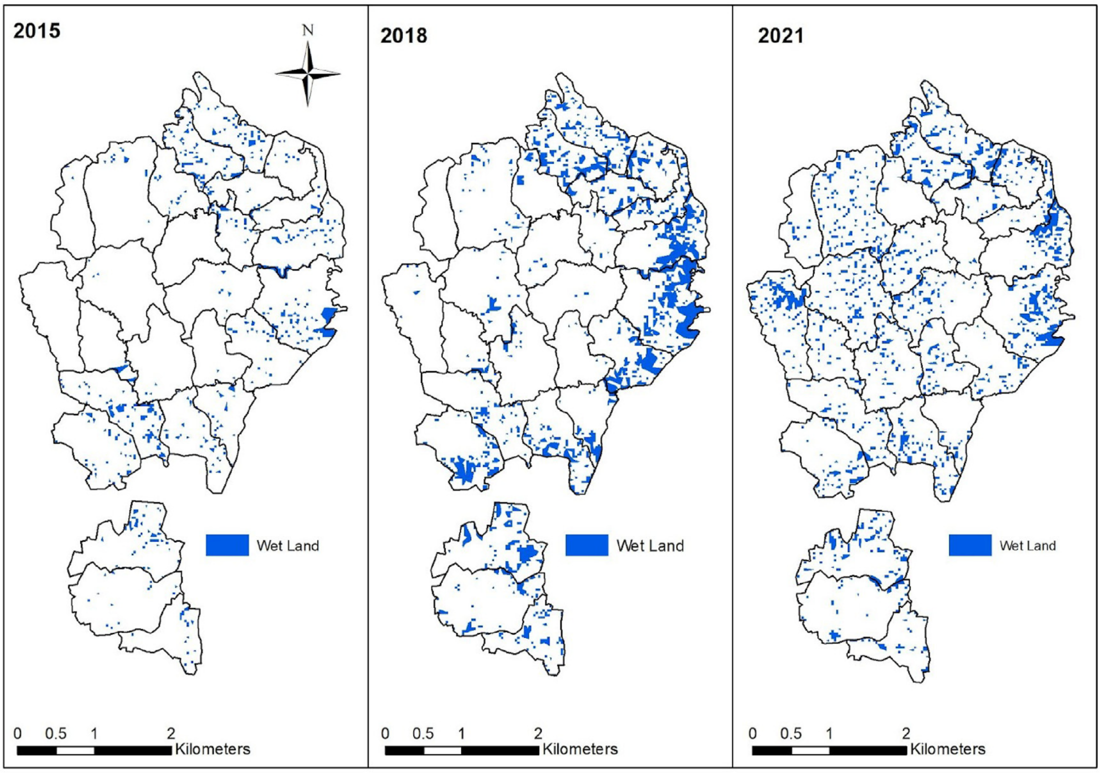


**Figure 9.** Spatio-temporal variation of wetland.

**Table 5.** Summary Statistics of Land use and Land Cover.

| Land use Class | 2015 (ha) | Changes % (2015–2018) | 2018 (ha) | Changes % (2018–2021) | 2021 (ha) | Changes % (2015–2021) |
|---|---|---|---|---|---|---|
| Bare land | 268.71 | 91% | 508.28 | -32% | 346.41 | 29% |
| Forest cover | 1256.55 | -66% | 432.61 | -26% | 321.32 | -74% |
| Settlement | 100.77 | 450% | 553.20 | 54% | 850.24 | 745% |
| Wet land | 68.39 | 188% | 197.08 | -11% | 175.63 | 157% |

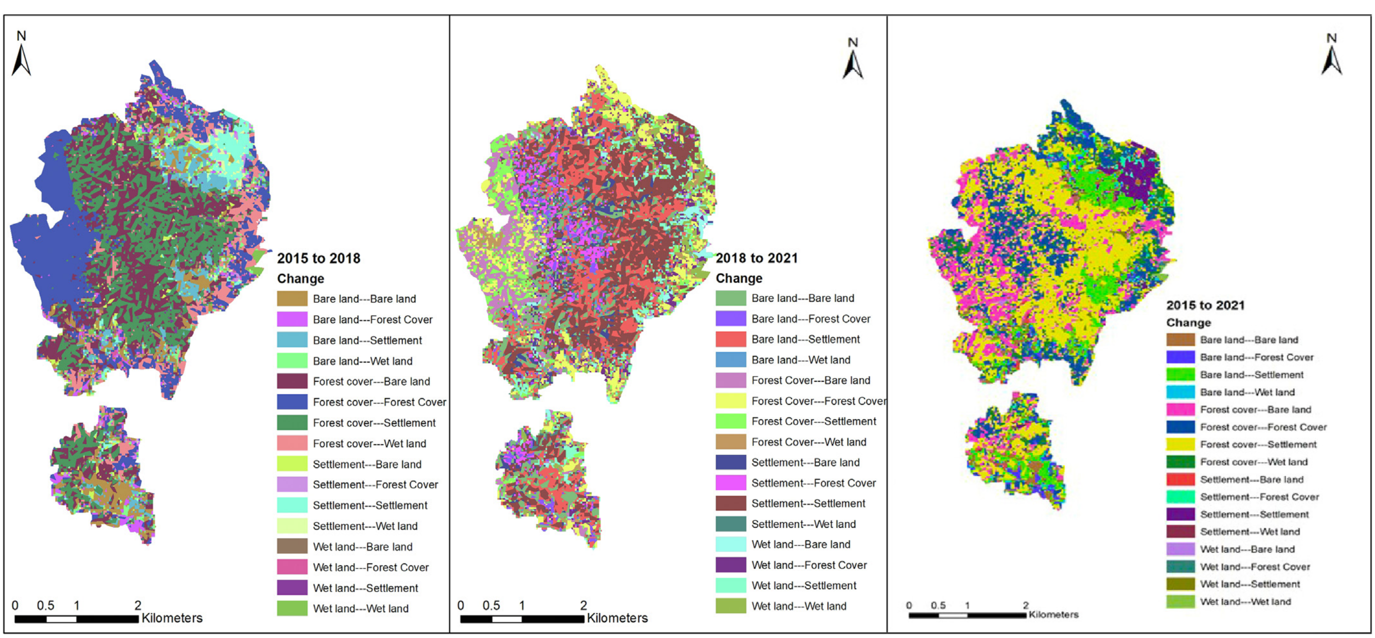


**Figure 10.** Land use Land Cover Transformation Map.

**Table 6.** Transitional probability matrix of LULC change detection.

| Transition Period | Land Use Types | To (Unit: Hectare) | | | | |
|---|---|---|---|---|---|---|
| | | Land cover classes | Bare land | Forest Cover | Settlement | Wetland |
| **2015 to 2018** | From (Unit: Hectare) | Bare land | **118.17** | 37.23 | 81.74 | 30.35 |
| | | Forest cover | 361.79 | 364.62 | **402.25** | 123.83 |
| | | Settlement | 17.80 | 12.54 | **51.79** | 18.21 |
| | | Wet land | 13.35 | 15.37 | **16.18** | 23.47 |
| **2018 to 2021** | | Bare land | 156.61 | 53.41 | **282.06** | 18.61 |
| | | Forest Cover | 113.72 | **151.35** | 106.43 | 57.46 |
| | | Settlement | 50.18 | 67.58 | **391.33** | 43.70 |
| | | Wet land | 24.28 | 47.75 | **68.79** | 55.03 |
| **2015 to 2021** | | Bare land | 53.82 | 31.16 | **165.11** | 17.40 |
| | | Forest Cover | 272.35 | 259.80 | **587.19** | 133.14 |
| | | Settlement | 9.71 | 13.35 | **66.77** | 10.11 |
| | | Wet land | 8.49 | 15.78 | **30.75** | 13.35 |

forest covers for settlement which cause a dramatic increase of bare land. Subsequently, they converted the bare land into settlements, and thereby, we can see a reduction of bare land in the following years. Wetland in the camp area increased rapidly-around 3 times from the year 2015–2018, however, the trend slowed after the year 2018.

We can see in Figure 5 that there is an inverse relationship between forest cover and settlement where the trend of settlement establishment within camp boundary has been rising since the influx (745%), parallelly, forest cover is declining. Though a portion of the western part of Kutupalong was covered by forest in 2018 (Figure 6), it is observed that mixed land use classes dominated by settlements in 2021 (Figure 7). Therefore, it is obvious that the surrounding environment of the campsite is affected by arranging accommodation for newly arrived refugees.

On the other hand, the percentages of forest cover have been decreasing parallelly compared to the increasing number of settlements since the influx in 2015 (e.g. 74% reduced from the year 2015–2021), which is alarming for the host environment, ecosystem, and wildlife habitat. From the period 2015 to 2018, the reduction rate was the highest (around 66%) which was devastating to the host environment. In this period, Rohingya refugees cut down a huge number of trees to make new settlements. After taking some measures in 2018 such as providing Cylinder Gas to every Rohingya household, the deforestation rate was reduced by 40% in 2021. Furthermore, different organizations have been trying to improve the environmental condition by planting trees in the camp area.

After the influx of Rohingya refugees in this area, the bare land increased by around 91% after cutting down trees as well as occupying wetlands (Figure 8). The camp area is becoming a desert where the temperature is rising and Rohingya people are suffering from Urban Heat Island (UHI) phenomenon. We also notice a dramatic expansion of wetland (Figure 9) from the year 2015–2021 (157% increase in wetland). Digging well and harvesting waters for thousands of refugee peoples expanded the wetland dramatically. Though wetland became double from the year-2015 to 2018, the rate was reduced by about 11% in 2021 (Table 5) as some portions of wetland were used as small-scale agriculture farms.

Human interventions cause the transformation of one land cover class to another. After the influx of the Rohingya refugees, certain land-cover classes converted to other classes (Figure 10). After analyzing the transitional probability matrix (Table 6) from 2015 to 2021 based on selected

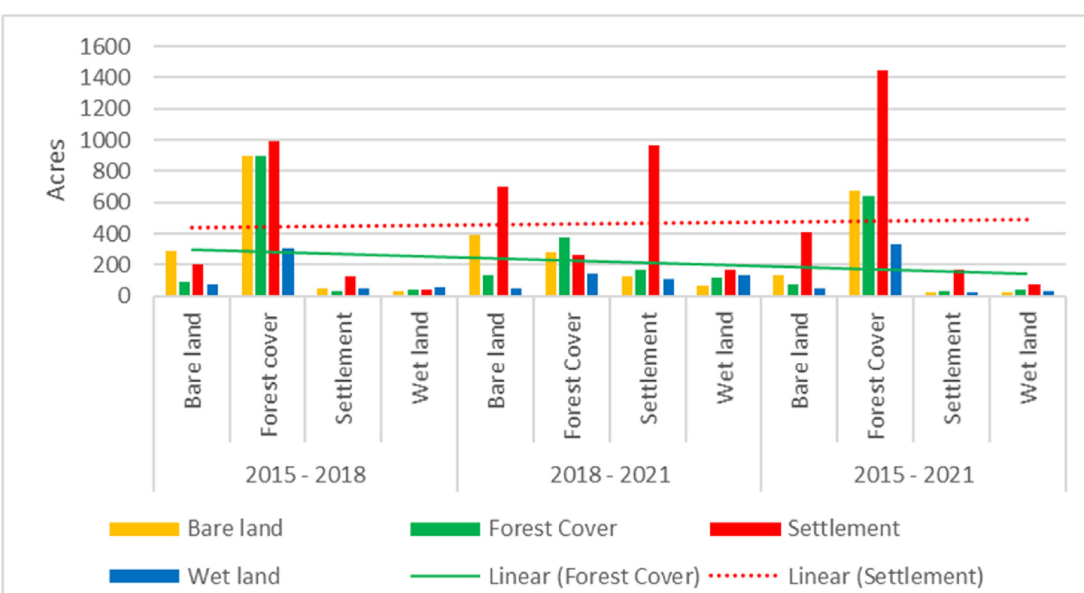


**Figure 11.** Relative changes of LULC

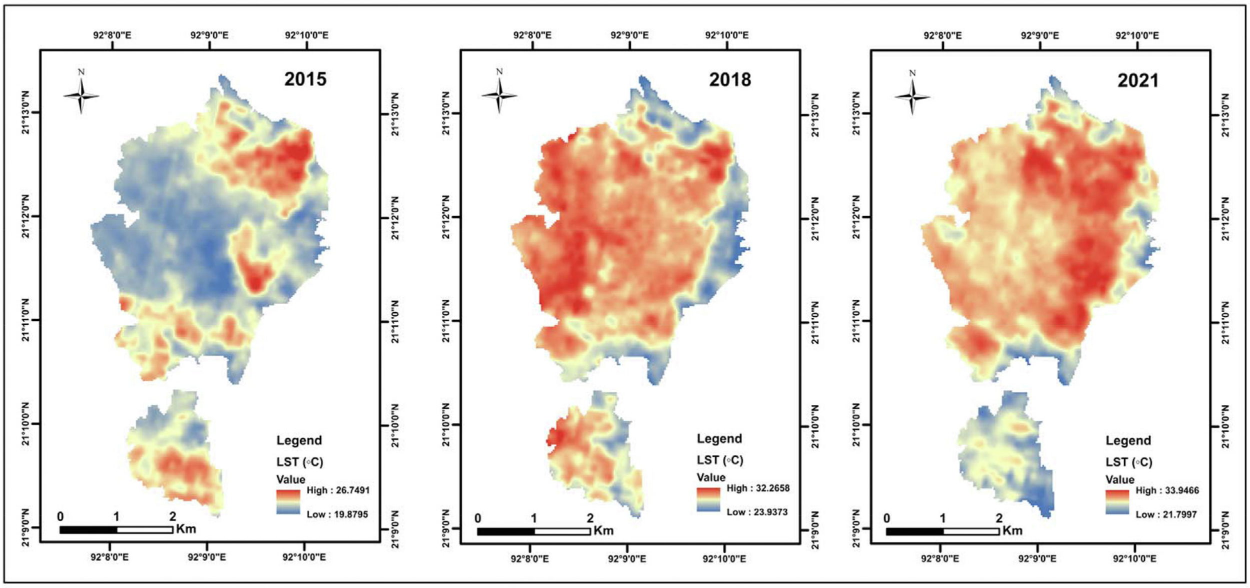


**Figure 12.** Distribution of LST in the study area from 2015 to 2021.

four types of land uses, it is intelligible that the settlements/built-up areas are the dominant land cover-class. During the 2015–2018 period, around 71% of forest cover was converted to other land uses where only 48% of settlement has converted to others. Furthermore, bare land became unused during this period (2015–2018). However, from the year 2018–2021, we can notice the dominance of built-up areas in the campsite (Figure 11).

### 4.1. Spatial variations of land surface temperature

Land Surface Temperature map of three years- 2015, 2018, and 2021 illustrate the spatial distribution of LST where red color indicates the highest and blue color indicate the lowest temperature (Figure 12). The distribution patterns revealed that the temperature has been gradually increasing in the last 6 years as the huge deforestation has occurred and the built-up area has increased due to the Rohingya influx. Figure 13 shows that the average temperature increases 6 times higher during 2015–2018 rather than the 2018–2021 time period where the rate is 0.06% during 2015–2018 and 0.01% during the following period.

The spatiotemporal change in LST over the study period is the result of an unplanned massive Rohingya influx and the allowance of the continuous destruction of forest land and the rapid development of settlements around the study area. Figure 14 demonstrates the maximum and minimum LST variation in built-up and vegetation classes from 2015 to 2021. The maximum LST for the built-up area has increased linearly during this period. The LST also increased significantly but the rate is slightly lower during the 2018 to 2021 period than the 2015–2018 period as the Rohingya influx mostly occurred in 2017 and the rapid deforestation took place at the same time. On the other hand, the minimum LST also increased for both built-up and forest cover areas, and the peak time was in 2018, then slightly decreased in 2021, as there are numerous local and international NGOs who are supporting and promoting green environment and renewable energy.

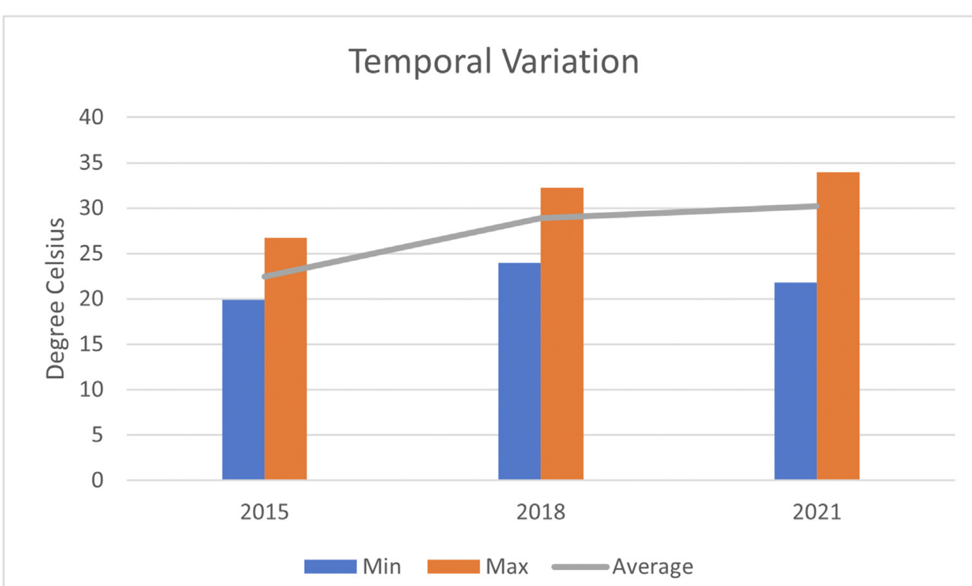


**Figure 13.** Variation of minimum, maximum and average LST over the year from 2015 to 2021.

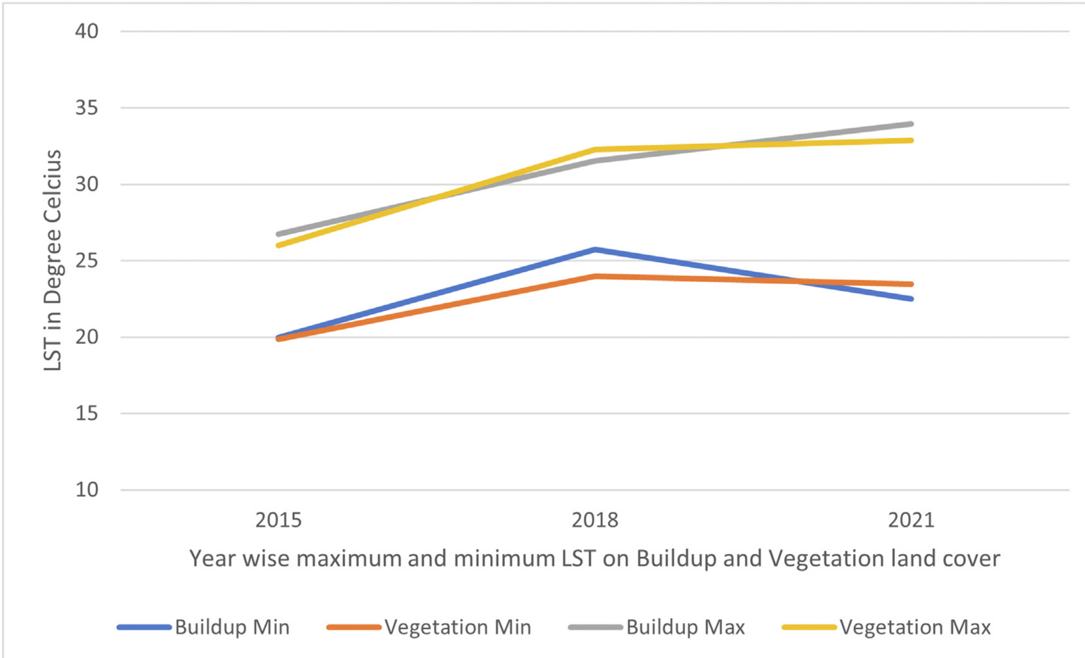


**Figure 14.** Year-wise maximum and minimum LST for LULC.

## 5. Conclusion & recommendations

The study reveals that the area has been undergoing a dramatic land use land cover change because of the Rohingya refugee influx after 2015. The forest covers have been transformed into different land uses, especially into settlements which are destroying the former balanced ecosystem rapidly. About 74% of forest covers were cleaned-up and replaced by settlements neglecting the consequences on the host environment. The increase of the settlement coverage is about more than seven times (7.45 times) since 2015, is an instant threat to the host environment and wildlife as it is causing huge deforestation. From 2015 to 2018 the area has experienced about 71 percent of its forest cover loss, where 32 percent was replaced by the settlements, 29 percent as bare lands, and the other 10 percent is replaced by water bodies to meet the residents need. The results also represents the dependence of the Rohingya refugee people on the forest resources not only for fuel (wood) but also cleaning up the forest coverage for other necessary uses like making ponds, roads and cleaning up the surrounding area they are living. These anthropogenic intervention creating a drastic change on land cover and the average land surface temperature (22.43 °C in 2015, 28.92 °C in 2018 and 30.22 °C) in 2021 on average, which is a great concern to protect the environment. The study also suggests a periodic study of LULC and LST to understand the ongoing phenomenon and future consequences to track the dramatic environmental degradation and deterioration of human-environment interaction for understanding the necessary actions to take. Simulation of the local environment based on LULC changes can be done in future work to understand the future consequences of such dramatic change in LULC in the host environment, which will help the concerned authority and humanitarian organization to take action and manage the program in a way which will minimize the impact on the host environment.

## Declarations

### *Author contribution statement*

Syed Alimuzzaman Bappa; Md Didarul Islam, M.S: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data.

Tanmoy Malakar: Contributed reagents, materials, analysis tools or data; Wrote the paper.

Md Rimu Mia: Performed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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### *Data availability statement*

Data will be made available on request.

### *Declaration of interests statement*

The authors declare no conflict of interest.

### *Additional information*

No additional information is available for this paper.

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