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Detecting Vegetation Disturbance in Kutupalong Rohingya Camp Area, Ukhia using LandTrendr Model

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Abstract: *This research emphasized on "Detecting Vegetation Disturbance in Kutupalong Rohingya Camp Area, Ukhia using LandTrendr Model". It mainly emphasized on the identification of pixel-based magnitude and direction of changes in vegetation cover due to disturbances caused by the Rohingya inhabitants based on Normalized Difference Vegetation Index derived from Landsat satellite imageries from 1984 to 2024. Ukhia is an Upazila located under Cox's Bazar district, is home to a substantial natural environment and vegetation cover. However, the local ecosystem and ecology have experienced considerable changes due to intensified human activities, including the establishment of large Rohingya refugee camps, illegal logging, and the impacts of climate change. Randomly selected reference points from camp area indicated a substantial decline of NDVI value (magnitude) from 0.8 to 0.1 which indicates a significant forest loss for the year of 2017 and 2018 which was not recovered in the subsequent years anymore. Hence, there is an abrupt or structural changes occurred in vegetation cover due to identified vegetation disturbance. For most of the sites, RMSE value was lower than 0.05 which indicates a better performance of the fitted LandTrendr model. It has been observed that severe vegetation loss and moderate vegetation loss occupy 16350 hectares and 53456 hectares including 24.99 % and 72.39% respectively regarding the total percentage of vegetation disturbance area. This research can give a proper direction to the concerned authorities in terms of identifying the sites where vegetation disturbances are continuously occurring including their magnitude and direction of change.*

Keywords: vegetation disturbance, LandTrendr, RMSE, magnitude, recovery

Introduction

In Bangladesh's Cox's Bazar District, the study of vegetation disturbance in Ukhiya Upazila is crucial for both the ecology and the economy. Significant changes in land use and vegetation cover have occurred in this region, which consists of a varied mix of natural forests, agroforestry regions, and refugee communities. Rapid population increase, resource extraction, and land conversion are some of the factors that have

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hastened vegetation loss and disturbance, which has an effect on ecosystem health and biodiversity (Quader 2019). Following increased persecution in a nation increasingly controlled by the army-backed government, the Rohingya people, a predominantly Muslim ethnic community who had lived in Myanmar's Rakhine area for millennia, have fled to Bangladesh (Hassan et al. 2018). Human actions and interactions with the environment cause environmental change. It is facing significant problems due to multiple factors, including population growth, environmental exploitation, deforestation, inappropriate land use, and human activity. Changes in land use and land cover are the primary causes of environmental change (Riebsame et al., 1994).

The Rohingya refugee issue is receiving attention from the international community. Millions of refugees from neighboring Myanmar State were escaping into Bangladesh out of fear of religious and ethnic persecution (Imtiaz 2018). Due to excessive strain on natural resources and other human-caused issues, the forest, water, and land systems in Ukhiya are fast deteriorating following the influx of Rohingya refugees. A significant contributing cause to the drastic local environment and ecological change is the accommodation of the Rohingya refugees and their expanding population, as more forest cover areas are being destroyed to make way for the construction of homes for them (Hossain and Moniruzzaman, 2021). Remote Sensing data and techniques can assist to identify the temporal and spatial distribution of vegetation losses for this area. The aim of this research is to investigate and detect disturbances in the vegetation of the study area including pixel-based changes in the magnitude and direction of vegetation disturbances using the Normalized Difference Vegetation Index (NDVI) derived from Landsat satellite imagery spanning 1984 to 2024.

Why Vegetation Disturbance through LandTrendr Model

Ukhia is an Upazila of Cox's Bazar district in Bangladesh, including a significant amount of natural environment and forest cover. However, the local ecology and ecosystem have undergone significant alteration as a result of recent intensified human activities, including massive refugee camps, illicit logging, and climate change. Despite the region's previous abundance of forest cover, which covered 50% of the land, land cover has changed significantly over the past 20 years, with around 13% of that forest cover now being used for other purposes (Hossain and Moniruzzaman, 2021)

The necessity to comprehend and lessen the environmental effects of swift land-use changes is the driving force for the investigation of vegetation disturbance in Ukhiya

Upazila, Cox's Bazar District. Due to population growth, agricultural expansion, and infrastructure development, the region which is home to one of the biggest refugee communities in the world has seen severe strain on its natural resources. Together, these elements lead to deforestation, deterioration of forest quality, and biodiversity loss, all of which are harmful to the ecosystem locally and globally (Ahmed et al., 2019).

About 2.68% of the altered area is made up by Rohingya communities or refugee camps, while the Cams have also taken over the region's agricultural land, making up around 1.01% of Cox's Bazar's total agricultural land (Hossain and Moniruzzaman, 2021). Additionally, the construction of shelters on degraded hills has made soil erosion a widespread occurrence, hindering stream flows and decreasing the stream's ability to drain off surplus rains during the monsoon season, which causes landslides, flash floods, and damaging assets (Quader et al., 2020).

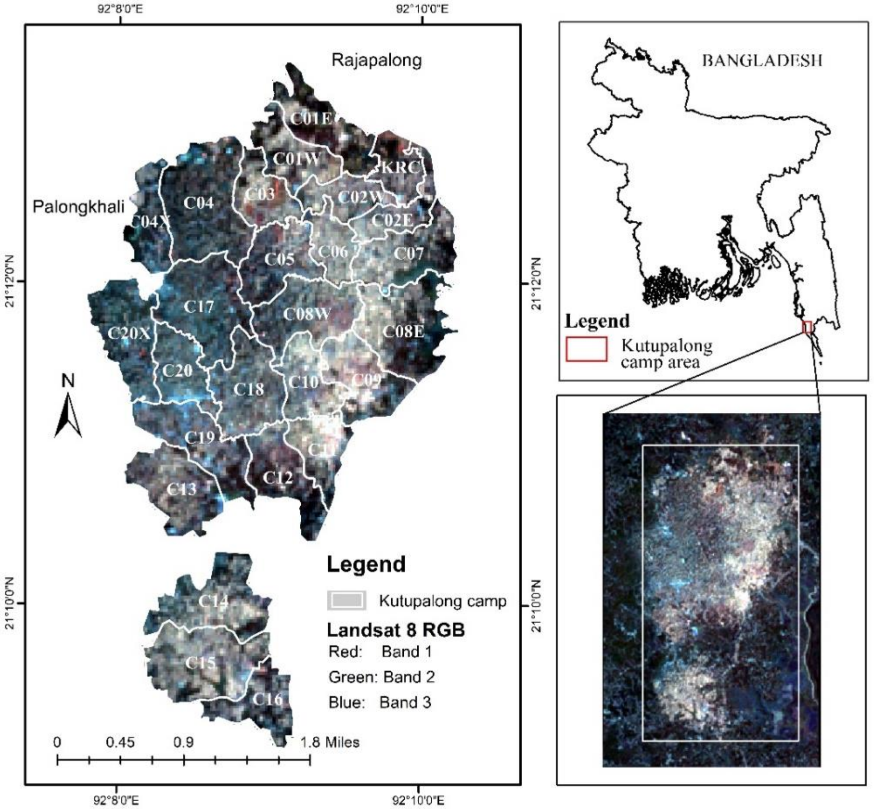
In order to evaluate possible effects on the local environment and ecosystems and to help planners, ecologists, administrators, and policymakers manage and create sustainable plans to counteract adverse effects on the environment and ecosystems as well as development activities, it is critical to acknowledge the LULC change pattern (Bappa et al., 2007). In the Kutupalong Mega Camp region, they disregarded the spatiotemporal changes in the ecology and environment and their effects on the local thermal environment (UNHCR, 2022).

The host environment suffered greatly as a result of the forest and natural resources being disregarded in the haste to find a location and provide shelter for the people in need. Deforestation and land degradation are accelerated by the current over use of natural resources mixed with the cumulative demands of recently arrived refugees in terms of unplanned development and land management (KC & Nagata, 2006). Therefore, monitoring and detecting forest disturbances on the study area is crucial, as vegetation is a key component of the local terrestrial ecosystem, contributing significantly to biodiversity and ecological balance (Mori et al., 2017). LandTrendr (Landsat-based detection of Trends in Disturbance and Recovery) is an effective model for detecting pixel-based changes in both the magnitude and direction of forest land cover alterations using continuous Landsat remote sensing data. Abrupt change in forest loss indicates the forest cover declines suddenly due to man-made or human interference whereas there is a chance to recover or regain it in the later years. On the contrary, Structural change indicates the forest loss where forest loss occurred is never recovered in the later years. This model can illustrate abrupt or structural changes of forest loss significantly (Kennedy et al., 2010).

Study Area

Ukhia, the study area, is a region in southeast Bangladesh that shares a border with Myanmar and is located in the Cox's Bazar district. The study area namely the Kutupalong Mega Camp comprises 26 individual camps covering an area of 4190 acres (16.96 sq. km) where the surrounding area is about 64,056 acres (259.22 sq. km). Currently, about 919,000 Rohingya refugees are living there. Since the inflow in 2015, the proportion of forest cover has been declining in tandem with the growing number of settlements (for example, 74% less from 2015–2021). This is concerning for the ecology, fauna, and host environment habitat. The greatest rate of decline occurred between 2015 and 2018 (around 66%), which had a disastrous effect on the host ecosystem. During this period, Rohingya migrants cut down large numbers of trees to establish new settlements. Deforestation decreased by 40% in 2021 as a result of actions taken in 2018, such as providing cylinder gas to all Rohingya households. Additionally, by planting trees in the camp area, many organizations have been attempting to ameliorate the environmental situation.

The removal of trees and the occupation of wetlands, the amount of bare land in this region grew by almost 91% due to the inflow of Rohingya refugees. Approximately 626,500 Rohingya refugees have been sheltered in the Kutupalong expansion site thus far. This problem has put a lot of pressure on the restricted natural resources on land and the surroundings of Ukhiya (Hossain 2022). The Cox's Bazar district's Kutupalong area is noteworthy for its varied natural resources and vegetated regions. Concern over changes in land cover and use at the Kutu Palong Rohingya Campsite has reportedly grown (Sakamoto et al. 2021). The local ecology and refugee population are negatively impacted socially and environmentally by the camp's quick growth and the corresponding rise in human activity (Hassan et al. 2018). Sustainable land use management and conservation efforts will be necessary to lessen the adverse effects and help us to comprehend the scope and ramifications of these changes as well as to recover from the present environmental degradation surrounding the refugee camps.



Map 1: Shows the Kutupalong Camp area in Ukhiya

The elimination of land cover, hill cutting, and excessive use of water resources in response to massive human requirements are examples of anthropogenic activities that have grown to be serious issues. These might harm natural resources and lead to a number of serious problems, including the loss of agricultural land, the extinction of animals and their habitat, and the instability of rural communities' economies.

Furthermore, illicit logging is a widespread occurrence these days to satisfy the need for wood as fuel for both locals and refugees. In addition to destroying the local forest cover and upsetting the natural balance, these human activities are also clearing large tracts of hillsides for the construction of infrastructure, the majority of which are new communities (Hassan et al., 2018).

Despite the Rohingya migration, not much research has been done to look at the environmental effects and the state of land use degradation surrounding the refugee camps (Hassan et al.,2018) Due to major human stressors from the Rohingya population and worldwide deforestation trends, the forest in this area is steadily losing quality and integrity (Hossain and Moniruzzaman, 2021). The Naf River is the principal river in the.91 square kilometers riverine basin. The Reju Canal and Enani Sea Beach are well-known for being popular tourist destinations (BBS, 2013). Women and children make up the great majority of Rohingya refugees in Ukhiya Upazila, with over 60% and 40% of them being under the ages of 18 and 12, respectively. (UNHCR, 2020).

Data and Methods

Mainly, this research utilized secondary data. Landsat remote sensing data were obtained from the LandTrendr model's data repository through its Application Programming Interface (API). The weakness of the model is that which specific type of Landsat data (i.e. Landsat 5, 7, 8) is used and in total, how many satellite images are used in model simulations are not known. However, based on temporal dimension and availability of images, it can be inferred that Landsat 5, 7, & 8 can be used whereas the spatial resolution is 30 m and total number of spectral bands are 7, 8, & 11 respectively. In this case, data are properly harmonized and standardized by the model as there are some differences in data settings for above mentioned Landsat data products. There are several steps were followed in the research process.

At first, the shapefile of Kutupalong Camp area was uploaded to Google Earth Engine (GEE). The shapefile path was then copied and pasted into the Area of Interest (AOI) section of the LandTrendr model. Various LandTrendr options and parameters were selected based on the vegetation characteristics of the study area. LandTrendr is a tool that performs temporal segmentation of spectral indices for remote sensing time series data, clearly illustrating disturbance and recovery trends, including their magnitude and stability. The model excludes noise, providing a fitted trend line and a Root Mean Square Error (RMSE) to assess how closely the projected values align with actual data. The entire process is depicted in Figure 1.

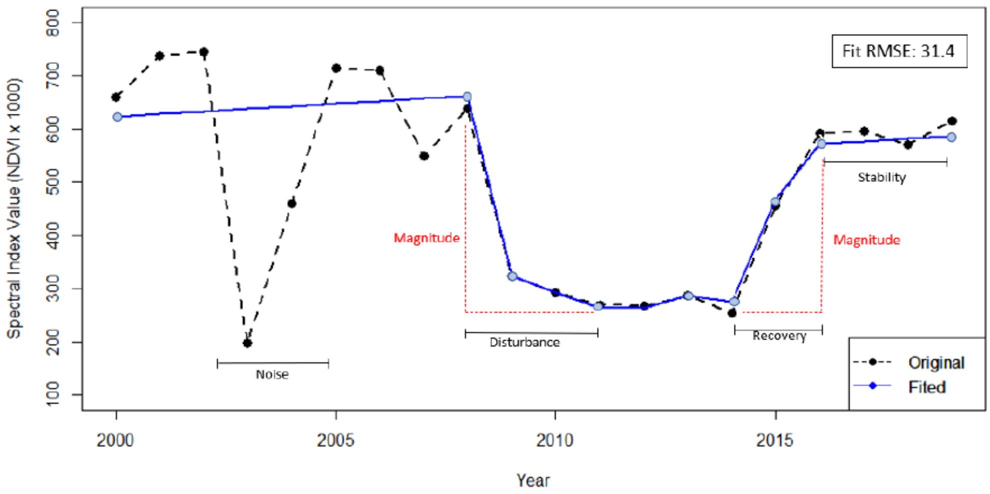


Figure 1: LandTrendr temporal segmentations and different properties (Kennedy et al., 2010)

Next, within the model's interface, the time range (e.g., year and month) was defined, and the NDVI index was selected from the indices list. Segmentation parameters were then adjusted according to table 1.

Table 1: LandTrendr temporal segmentations parameters including explanations (after Kennedy et al., 2010)

Segmentation Parameters	**Selected Values/operators**	**Explanation**
Max Segments	10	As forest disturbance might happen mostly in the few specific years according to above mentioned literatures to the study area, so there was less chance to develop more than ten segments in the fitted time series within the studied time frame.
Spike Threshold	0.9	Threshold 0.9 includes all dampening of the spikes whereas 1 means no dampening.
Vertex Count Overshoot	3	As max segments were 7, so vertex count overshoot can be 3 in terms of its quantity of max segments.

Prevent One Year Recovery	true	One year recovery of forest disturbance is not mentionable that's why it is excluded from the model simulation.
Recovery Threshold	0.25	For disallowing forest disturbance recovery in a short time, the threshold value 0.25 is selected whereas threshold value 1 indicates no segmentation.
p-value Threshold	0.05	As the 95% significance level is statistically justified that's why p-value threshold 0.05 was fixed whereas if the p-value of the fitted model exceeds this threshold, then the current model was discarded.
Best Model Proportion	0.75	The value 0.75 was fixed to exclude the most vertices having a p-value that is at most this proportion away from the model with lowest p-value.
Min Observations Needed	7	There is a chance to decrease the amount of satellite images (observations) due to cloud presence in Landsat products so that these minimum observations were fixed.

From the asset overlay options, the path of the previously uploaded study area shape file in GEE was specified and verified. Using the change filter options, disturbance images were added to extract information on the year of detection, magnitude, and duration of changes. Reference points were included under pixel time series options to generate temporal segmentations and obtain details such as the year of disturbance, its magnitude, and recovery period for specific pixels. Finally, the output images, time-series figures, and corresponding .csv files were downloaded through the model's download options.

Results and Discussion

The Figures 2 and 3 present NDVI time-series trends for 20 different camps in the study area from 1988 to 2024. Each graph displays the original NDVI values (solid line) and the fitted trend (dotted line), along with the Root Mean Square Error (RMSE), which quantifies the accuracy of the fitted model. The general trend across all camps indicates relatively stable NDVI values before 2017, followed by a sharp decline due to significant land-use changes associated with the Rohingya refugee influx. The magnitude of NDVI reduction varies among camps, with some showing slight post-2020 recovery, while others remain at historically low levels.

Camp 1E (RP:1E) and Camp 1W (RP:1W)
Both camps exhibit a stable NDVI pattern between 0.4 and 0.8 until 2017, indicating dense vegetation cover. However, a sharp NDVI decline post-2017 reduces values to approximately 0.2, suggesting extensive deforestation. The RMSE values for Camp 1E (0.039) and Camp 1W (0.043) indicate a good fit for the model, capturing the abrupt vegetation loss. This drop coincides with the refugee settlement expansion, where large areas of forest were cleared for housing and other infrastructure.

Camp 2E (RP: 2E) and Camp 2W (RP: 2W)
Camp 2E exhibits a gradual NDVI decline over time, followed by a pronounced drop post-2017, with an RMSE of 0.067, the highest among all camps, suggesting high variability in vegetation cover loss. Camp 2W, in contrast, experiences a more abrupt NDVI drop around 2017, stabilizing at a lower level. The RMSE of 0.036 suggests the fitted model closely follows observed trends. The significant reduction in NDVI values confirms that deforestation in these areas has been severe and ongoing.

Camp 3 (RP: 3) and Camp 4 (RP: 4)
Both camps maintain stable NDVI values up to 2017, after which they experience a dramatic decline. The RMSE values for Camp 3 (0.045) and Camp 4 (0.041) indicate a strong model fit, capturing the sudden environmental impact. The decline aligns with increased refugee settlement activity, which led to massive forest clearance and land degradation. The post-2018 stabilization at lower NDVI values suggests a lasting change in land cover.

Camp 4 Extension (RP: 4 Ext.) and Camp 5 (RP: 5)
Camp 4 Extension initially shows an increasing NDVI trend, likely due to vegetation growth, but experiences a sharp drop post-2017, with an RMSE of 0.038. This pattern suggests that although reforestation efforts may have been attempted, they were insufficient to counteract large-scale deforestation. Camp 5 exhibits a significant decline around 2017, followed by a minor recovery post-2020, though NDVI levels remain significantly lower than before. The RMSE value of 0.040 confirms the trend reliability.

Camp 6 (RP: 6) and Camp 7 (RP: 7)
Camp 6 maintains high NDVI values (~0.8) until 2017, followed by a drastic drop, with an RMSE of 0.039. Camp 7 follows a similar pattern but has a higher RMSE of 0.059, indicating greater fluctuations in NDVI values. Both camps display persistent low NDVI post-2017, reflecting continued vegetation loss and lack of significant recovery.

Camp 8E (RP: 8E) and Camp 8W (RP: 8W)
Both camps experience a gradual NDVI decline over time, with a sharp decrease around 2017. The RMSE values for Camp 8E (0.057) and Camp 8W (0.055) indicate that the fitted models effectively capture the observed trends. The data suggest that while natural vegetation loss was occurring before 2017, the refugee settlement expansion accelerated the deforestation process significantly.

Camp 9 (RP: 9) and Camp 10 (RP: 10)
Camp 9 exhibits moderate fluctuations in NDVI before 2017, followed by a sharp decline that stabilizes at a much lower level, with an RMSE of 0.049. Camp 10 follows a similar trajectory, with an RMSE of 0.055, confirming significant vegetation loss. The stability of NDVI at lower levels post-2018 indicates that reforestation efforts in these areas have been minimal or ineffective.

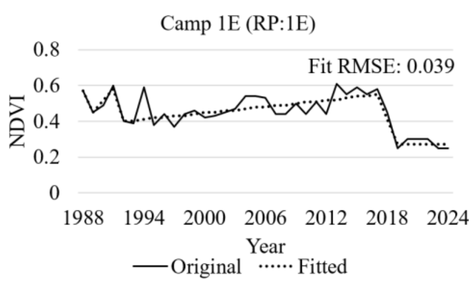
Camp 11 (RP: 11) and Camp 12 (RP: 12)
Both camps exhibit steep declines in NDVI post-2017, with NDVI values remaining consistently low afterward. Camp 11 has an RMSE of 0.038, while Camp 12 has an RMSE of 0.046, reflecting slight variations in deforestation patterns. The sharp decline coincides with intensified land conversion for refugee settlements, leading to deforestation and land degradation.

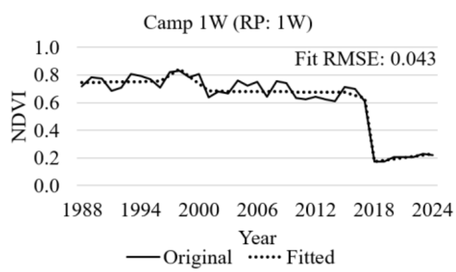
Camp 13 (RP: 13) and Camp 14 (RP: 14)
Camp 13 follows the general trend of stable NDVI before 2017, followed by a steep drop, with an RMSE of 0.049. Camp 14 exhibits a similar pattern of rapid vegetation loss, with an RMSE of 0.036, indicating a good model fit. Unlike most other camps, Camp 14 shows a slight post-2020 recovery, though NDVI values remain significantly lower than pre-2017 levels.

Camp 15 (RP: 15) and Camp 16 (RP: 16)
Camp 15 exhibits the most severe NDVI drop, decreasing from 0.6 to below 0.2, with an RMSE of 0.069, the highest among all camps, indicating extreme environmental degradation. Camp 16 follows a similar pattern of NDVI decline, with an RMSE of 0.047, confirming a drastic loss of vegetation cover. These camps represent the worst-affected areas, where large-scale deforestation has led to near-total loss of natural vegetation.

Across all 20 camps, the most significant trend is the sharp NDVI decline post-2017, aligning with the massive deforestation associated with refugee settlement expansion. The most affected camps exhibit little to no NDVI recovery, suggesting persistent environmental degradation. While a few camps, such as Camp 5 and Camp 14, display minor post-2020 recovery, overall vegetation loss remains extensive. The low RMSE values across all models confirm the reliability of the fitted trends, making them suitable for assessing vegetation disturbances.

There is a similar pattern in RMSE value for all 16 reference points (RP) showing a value of less than 0.05 except 4 reference points such as; RP: 2E, RP: 7, RP: 8E & RP: 15. The findings emphasize the urgent need for reforestation initiatives, sustainable land-use management, and conservation strategies to mitigate long-term ecological damage. Without intervention, the continued loss of vegetation could exacerbate environmental challenges such as soil erosion, water scarcity, and habitat destruction in the study area. Future studies should focus on monitoring NDVI recovery trends and evaluating the effectiveness of afforestation programs to restore degraded lands.





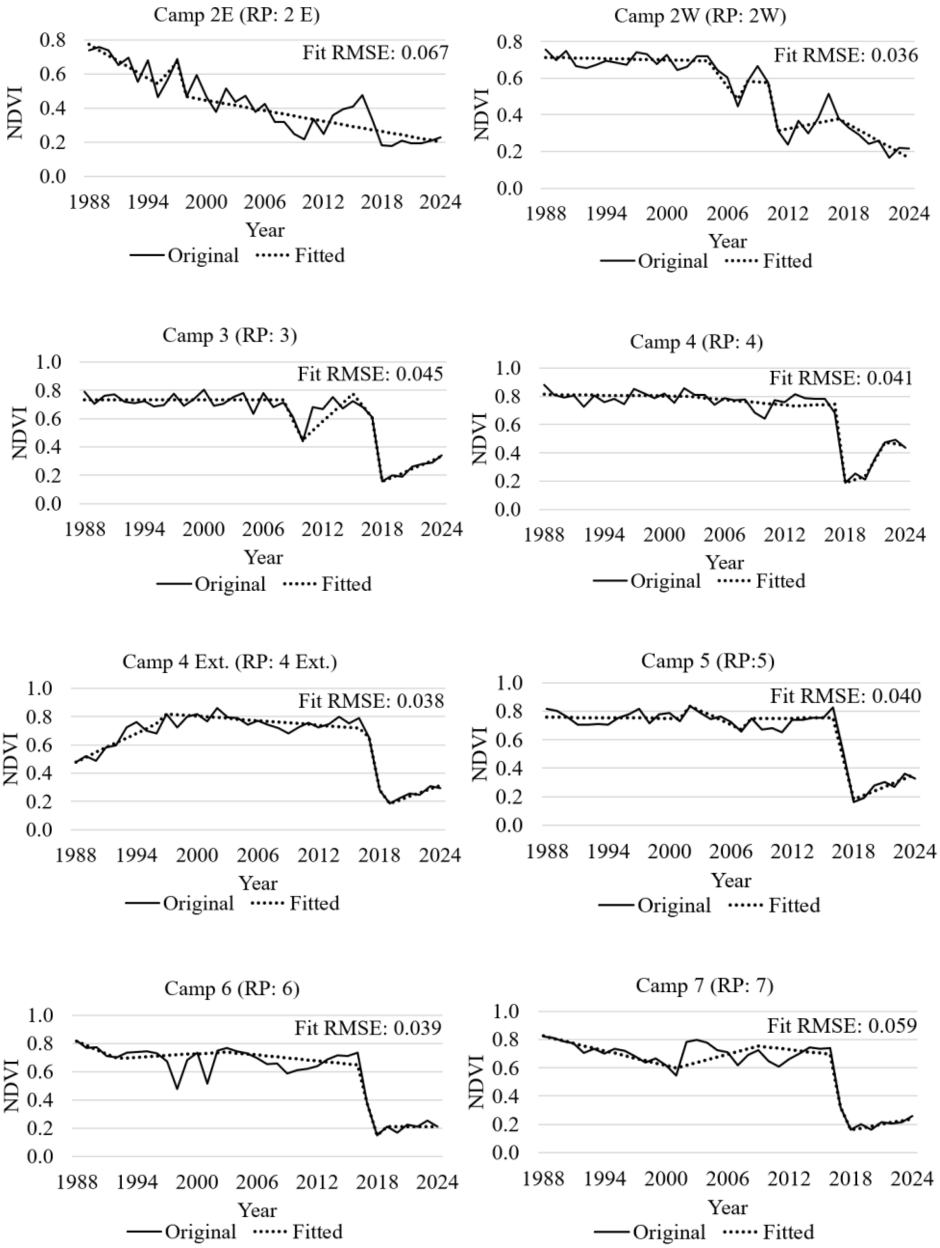


Figure 2: Shows the referece points for vegetation change magnitude, trend, and recovery scenarios applying LandTrendr model

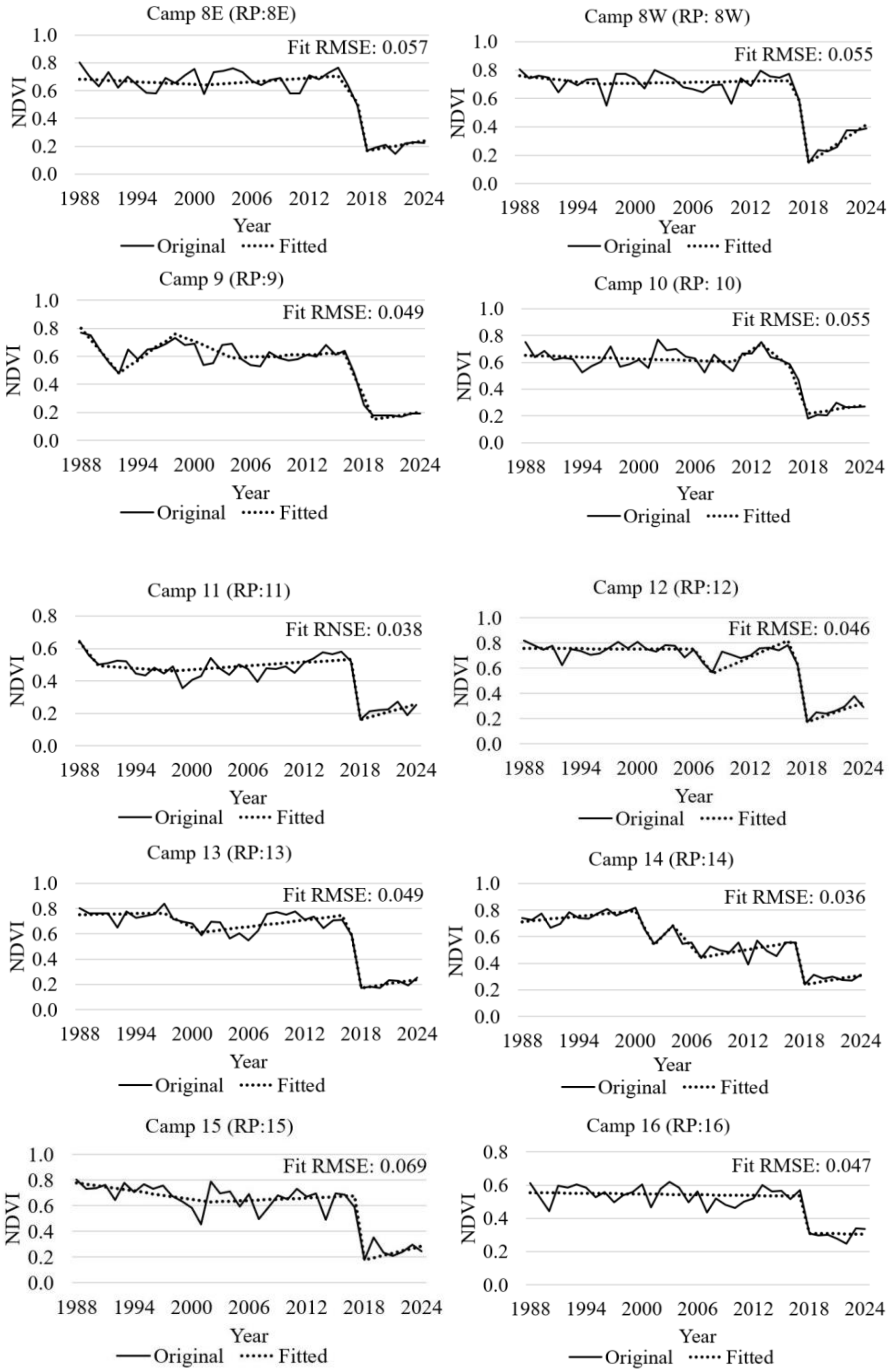


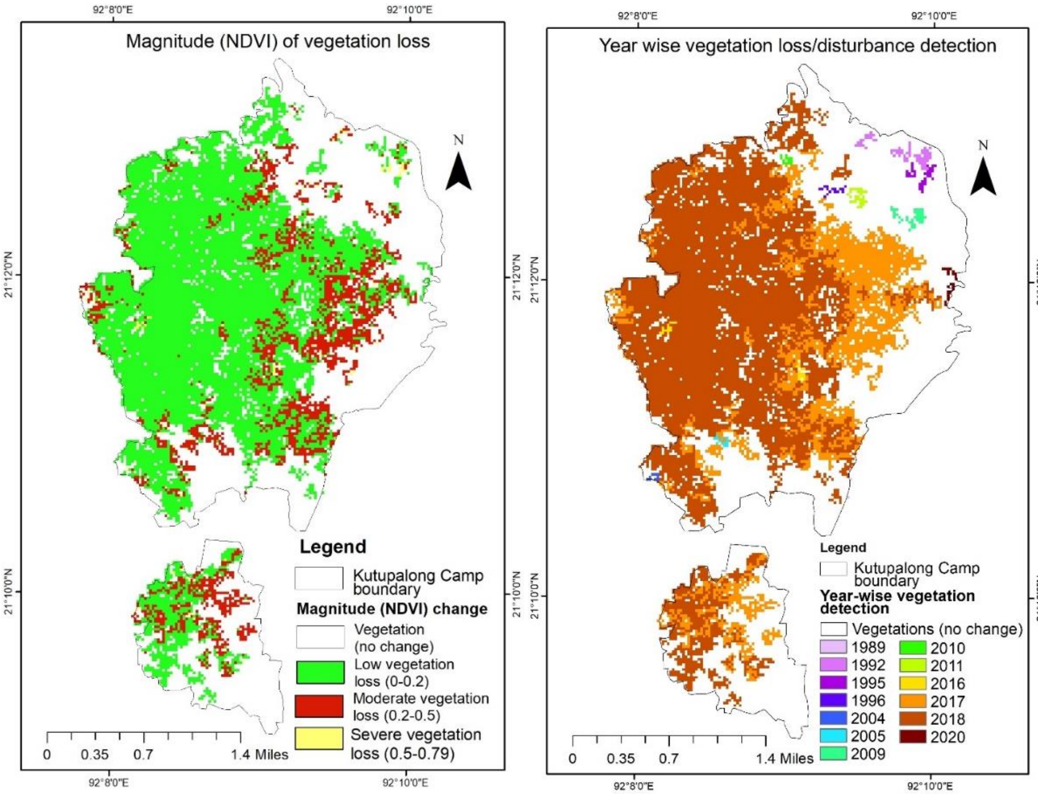
Figure 3: Shows the referece points for vegetation chnge magnitude, trend, & recovery scenerios applying LandTrendr model

Magnitude of Change in NDVI Derived from LandTrendr Model

Map 2(a) illustrates the magnitude of vegetation loss in terms of NDVI within the Kutupalong Camp boundary and its surrounding areas. The map provides a spatial representation of vegetation changes over time, indicating areas that have experienced varying degrees of vegetation loss. The study area is delineated with a white outline, showing the extent of the Kutupalong refugee camp and its surroundings. The legend categorizes the magnitude of NDVI change into four distinct classes. Areas with no significant vegetation loss are represented in white, indicating stable vegetation cover. Green areas depict low vegetation loss (NDVI change between 0 and 0.2), suggesting minor disturbances that have not significantly altered the overall vegetation structure. Red areas signify moderate vegetation loss (NDVI change between 0.2 and 0.5), indicating increasing deforestation, likely due to settlement expansion, resource extraction, or agricultural activities. Yellow areas highlight severe vegetation loss (NDVI change between 0.5 and 0.79), representing regions that have undergone extensive deforestation, possibly due to large-scale land clearing for infrastructure and human settlement.

The map shows a predominance of green areas, indicating that a significant portion of the region still retains its vegetation with minimal disturbances. However, clusters of red and yellow pixels, representing moderate to severe vegetation loss, are concentrated primarily within the camp boundary and extend towards the southern and eastern portions of the study area. The presence of localized yellow areas suggests that some regions have suffered extreme deforestation, which could be attributed to population pressures and the demand for land and resources within the camp. The spatial pattern of vegetation loss suggests that the deforestation process is not uniform across the region. Some areas remain relatively undisturbed, whereas others have experienced significant degradation, likely influenced by factors such as population density, accessibility to forested regions, and the intensity of human activities.

The observed vegetation loss within the Kutupalong Camp boundary aligns with reports on the environmental impacts of the Rohingya refugee influx. The widespread deforestation is consistent with the need for firewood, shelter materials, and agricultural expansion to sustain the displaced population. Although large portions of the region still maintain ecological stability, the presence of moderate to severe vegetation loss highlights the necessity for immediate intervention. Without sustainable land management strategies, continued deforestation may exacerbate environmental challenges such as soil erosion, biodiversity loss, and water scarcity. The findings suggest that conservation efforts, such as afforestation programs, controlled land use policies, and the provision of alternative energy sources, are essential to mitigate further environmental degradation. Future research should focus on long-term NDVI monitoring to assess vegetation recovery patterns and evaluate the effectiveness of restoration and conservation initiatives in the region.



Map 2(a) Magnitude (NDVI) of vegetation loss and Map 2(b) Year-wise vegetation loss detection from 1984 to 2024 for a period of 40 years

Source: NASA LP DAAC at the USGS EROS Center, derived from LandTrendr Model

Map 2(b) illustrates the year-wise detection of vegetation loss/disturbance within the Kutupalong Camp boundary and surrounding areas. The map uses a color-coded system to indicate the timeline of vegetation loss, with different shades representing years ranging from 1989 to 2020, while white areas signify no significant vegetation change. The darker shades, concentrated mainly in the western and southern regions, indicate areas where vegetation loss began earlier, particularly in 2004, 2005, and 2009, suggesting progressive land degradation. The eastern portion of the map exhibits more recent disturbances, particularly from 2016 to 2020, aligning with the massive refugee influx and subsequent land-use changes.

The widespread disturbance in the western and southern section's suggests prolonged human activities such as deforestation, agricultural expansion, and settlement development over multiple decades. The more recent disturbances observed in the eastern and northern regions highlight accelerated land cover changes likely linked to the expansion of refugee settlements. The dominance of vegetation loss in 2017 and 2018 corresponds with the peak of the Rohingya migration, confirming the significant impact of human-induced deforestation.

The pattern of progressive vegetation loss underscores the urgent need for sustainable land management, reforestation efforts, and conservation policies to mitigate further environmental degradation. The expanding loss over time also suggests increasing pressure on natural resources, further emphasizing the necessity for intervention strategies, such as afforestation programs, controlled land use policies, and alternative livelihood options to reduce dependency on forest resources. Continuous NDVI-based monitoring will be essential to assess future trends in vegetation recovery and evaluate the effectiveness of conservation efforts in the region.

Table 2: Percentage of vegetation loss according to magnitude of NDVI

Magnitude (NDVI) class	Pixel Count	Area (in hectares)	Percentage (%)
No change	8103	50644	41.74
Low vegetation loss	140	875	0.72
Moderate vegetation loss	8553	53456	44.06
Severe vegetation loss	2616	16350	13.48

Table 2 presents the percentage of vegetation loss based on the magnitude of NDVI change, categorized into four classes: no change, low vegetation loss, moderate vegetation loss, and severe vegetation loss. The pixel count, corresponding area (in hectares), and percentage of total land cover are provided for each category, offering insight into the extent of vegetation disturbance in the study area.

The "No change" category accounts for 41.74% of the total area, covering 50,644 hectares, indicating that nearly half of the study region has retained its vegetation with minimal to no disturbance. Low vegetation loss, representing minor environmental disturbances, is observed in only 0.72% of the area (875 hectares), suggesting that areas experiencing gradual vegetation decline are relatively small. The moderate vegetation loss category accounts for 44.06% (53,456 hectares), making it the most dominant class, signifying significant forest and vegetation degradation across a large portion of the study area. Severe vegetation loss, affecting 13.48% (16,350 hectares), highlights areas where extensive deforestation or land-use conversion has occurred, likely due to settlement expansion, infrastructure development, and resource extraction.

The data clearly indicate that over half (57.54%) of the study area has undergone vegetation loss, with the majority categorized as moderate loss. The relatively high proportion of moderate and severe vegetation loss (57.54%) suggests substantial land degradation, particularly in areas affected by human activities, such as deforestation and refugee settlement expansion. Although 41.74% of the land remains unchanged, the predominance of vegetation loss, especially in the moderate category, highlights the ongoing environmental pressure on the region. These findings underscore the urgent need for reforestation, afforestation, and conservation measures to mitigate further degradation. Future studies should focus on long-term NDVI monitoring, sustainable land management practices, and policy interventions to ensure the restoration of affected ecosystems.

Table 3 presents the percentage of vegetation loss based on the year of detection, showing a temporal distribution of deforestation events. From 1989 to 2016, vegetation loss remained relatively low, with annual percentages ranging from 0.05% to 0.68%, indicating minimal disturbances over this period. A significant increase is observed in 2017, where 24.99% (17,662 hectares) of vegetation loss occurred, marking the beginning of extensive deforestation.

Table 3: Percentage of vegetation loss according to year of detection

Year of detection	Total pixel count	Area (in hectares)	Percentage (%)
1989	6	38	0.05
1992	77	481	0.68
1995	38	238	0.34
1996	16	100	0.14
2004	9	56	0.08
2005	13	81	0.11
2009	42	262	0.37
2010	13	81	0.11
2011	30	188	0.27
2016	29	181	0.26
2017	2826	17662	24.99
2018	8187	51169	72.39
2020	23	144	0.20

The peak of vegetation loss is recorded in 2018, accounting for 72.39% (51,169 hectares), coinciding with the major Rohingya refugee influx and large-scale land clearing for settlement expansion. By 2020, vegetation loss had significantly reduced to only 0.20% (144 hectares), suggesting a slowdown in deforestation, possibly due to conservation efforts or reduced land conversion.

The sharp increase in 2017 and 2018 highlights the severe environmental impact of human activities, particularly deforestation driven by the refugee crisis. The drastic loss of vegetation within two years underscores the urgency of reforestation initiatives, afforestation programs, and sustainable land-use planning to mitigate long-term ecological damage. While post-2018 vegetation loss appears minimal, ongoing monitoring is essential to assess whether the forest is recovering or if degradation persists at a lower rate.

Discussion

Within the study period of 40 years (1985 to 2024), only 13 years are detected by the applied model for vegetation loss. It is observed that substantial loss occurred during the year of 2017 and 2018. For few places, the loss happened in 1992, 2004, 2010, and

2011. From table 2, it has been mentioned that severe vegetation loss and moderate vegetation loss occupy 16350 hectares and 53456 hectares which are the 24.99 % and 72.39% respectively regarding the total percentage of change.

For every pixel where vegetation loss occurred that is not recovered in the later years due to clear-cutting of vegetation. Therefore, there is a structural change in vegetation cover. The pixels of no change area is in a stable condition because this area is closed to the border, the landscape is more undulated, and lower influx of Rohingya refugees. With this research, the applied LandTrendr model has been able to detect pixel based forest loss, its trends, magnitude of loss, and recovery scenario of vegetation loss.

Conclusion

The Rohingya Camp and its surrounding area is significant from ecological point of view because forest plays vital role for the maintenance of ecological balance of that particular area. The extent of vegetation loss due to Rohingya influx is very acute. If this trend continues, there will be a great chance of happening drastic impact in landscape ecology of that area. LandTrendr model has been able to identify the changes of vegetation precisely in pixel level without any information gap including continuous observations of satellite images. Therefore, the concerned authority will have the opportunity to gather information precisely that exactly in which pixel of the which sites of the study area is mainly vulnerable that will be identified and can take necessary steps on a priority basis. There is a key limitation of this model is the unclear documentation regarding the exact number of satellite images or observations used. Additionally, applying the output of this research, in the more vulnerable sites of the Rohingya Camp area regarding vegetation loss, some measures should be taken for minimizing the vegetation loss such as; afforestation in the cleaned part of the camp sites, create awareness among the local inhabitants to check further deterioration of the forest loss occurrence, a suitable land use planning can be applied, and existing legislations should be applied for minimizing indiscriminate forest cutting.

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