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Rohingya Refugee Camps and Forest Loss in Cox's Bazar, Bangladesh

An Inquiry Using Remote Sensing and Econometric Approaches

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Abstract

How do refugee camps impact the natural environment? This paper examines the case study of Cox's Bazar, Bangladesh, a district that hosts nearly 1 million Rohingya refugees in refugee camps. Using spatially explicit data on land-use / land cover and proximity to a camp boundary, the paper quantifies land-use changes across the district over time. To evaluate the extent to which the camps triggered additional forest loss, the analysis calculates total forest loss in the district and uses a difference-in-difference model that compares areas 0–5 kilometers from a camp boundary (treatment) to areas 10–15 kilometers away (control). The findings show that the rate of forest loss intensified near camps relative to the control area. The analysis reveals that areas experiencing camp-stimulated reductions in forest cover are also experiencing faster settlement expansion relative to the control area. Settlement expansion is largely concentrated in areas outside protected areas. This enhanced settlement expansion still occurs when pixels 0–1 kilometer from the camps are omitted, which is evidence that the results are not due to camp settlements expanding beyond the official camp borders. The results suggest that camps stimulate in-migration as Bangladeshis seek new economic opportunities and improved access to resources.

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Rohingya Refugee Camps and Forest Loss in Cox's Bazar, Bangladesh: An Inquiry Using Remote Sensing and Econometric Approaches*

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1. Introduction

In recent years, the number of quantitative studies focused on refugees and host communities has increased dramatically (Verme & Schuettler, 2021). Many of these studies seek to quantify the direct costs of hosting and challenges facing refugees with respect to employment (Alix-Garcia *et al.*, 2018; Fallah, Krafft, and Wahba, 2018), consumption (Maystadt and Verwimp, 2014; Kreibaum, 2016; Mahmud and Nalifa, 2020), health (Baez, 2011; Riley *et al.*, 2017; Chan, Chiu, and Chan, 2018; Jasmine *et al.*, 2020) and local prices (Alix-Garcia & Saah, 2010). More recently, there has been an effort to examine the impacts of the COVID-19 pandemic for refugees and hosts (Bukuluki *et al.*, 2020; Charney, 2020; Islam, Inan, and Islam, 2020; Shammi, Robi, and Tareq, 2020; Vishwanath, Alik-Lagrange, & Aghabarari, 2020).

Empirical analyses of the impacts of refugees on natural capital, however, remain limited. Natural capital is the stock of the planet's natural assets, including plants, animals, soil, minerals, air, water, and other renewable and non-renewable resources that yield ecosystem services, which are the benefits that people receive from nature. Human activities, including land-use that causes changes in land cover, can lead to the loss of natural capital stocks and reductions in the flow of benefits these stocks generate. Land-use / land cover (LULC) change is increasing due to natural disturbances and growing human activities (Abere, Adgo, & Afework, 2020; Elias, Seifu, Tesfaye, & Girmay, 2019; Lambin, Geist, & Lepers, 2003). However, the impacts of refugee camps on their surrounding natural environments remain understudied.

In this paper, we evaluate whether hosting a large refugee population in refugee camps causes changes in forest cover in Bangladesh, and if so, the specific causes of deforestation. We distinguish between two possible channels of impact. The first is the *direct impact of refugees*, the consequence of clearing land for the camp expansion, and of camp residents harvesting forest products for shelter and cooking fuel. We differentiate this from the *indirect impacts of hosting refugees,* which captures the influence refugee camps have on local markets, access to services, humanitarian investment, and consequently, local economic productivity and population distributions.

There are very few precedents for our work in the quantitative literature (Black & Sessay, 1997; Maystadt, Mueller, Van Den Hoek, & Van Weezel, 2020; Rahman, 2017; Salemi, 2021). Many of these past studies do not account for the endogeneity of areas selected for camps, nor do they account for counterfactual forest loss in the absence of the refugee population's arrival. Two previous studies estimate camp impacts in Sub-Saharan Africa using a quasi-experimental approach. First, Maystadt, Mueller, Van Den Hoek, & Van Weezel (2020) examine the land characteristics of large grid-cells that contain camp populations over the subcontinent. They find that larger camp populations increase the probability that the grid-cell experiences both forest loss and agricultural expansion, but they also find that larger camp populations lead to slightly higher vegetation density. Building on this study, Salemi (2021) examines higher-resolution grid-cells around refugee camps and finds that forest losses in response to camp openings are statistically significant but extremely small in magnitude. Our paper builds on this recent discourse by examining a case study with characteristics quite different from Sub-Saharan Africa, where land is relatively abundant and population densities are low. The environmental impact of camps may be quite different in Bangladesh, which is characterized by high population densities and low levels of in-tact natural lands.

Our case study focuses on the most recent arrival and encampment of Rohingya refugees in Cox's Bazar, Bangladesh. In late 2017, more than 740,000 Rohingya citizens of Myanmar fled violent persecution in their home villages and crossed into the Cox's Bazar region. Upon arrival, UNHCR, the Bangladeshi government, and their partners constructed and began servicing several large refugee camps, all within the southern half of Cox's Bazar. Some of the unanswered questions regarding the impact of this migration and the establishment of the refugee camps are: how much forest cover was lost within and outside the refugee camps? To what extent is the forest cover change around refugee camps comparable to other locations across Cox's Bazar district? What are the primary drivers of deforestation near the camps? Are Rohingya refugees directly causing forest cover loss in the region? Or has increasing economic activity associated with the refugee camps' presence driven forest change?

Remote-sensing data opens up new opportunities to investigate whether the areas near camps face higher rates of natural capital losses and whether camp residents primarily drive such transitions. Using the US Geological Survey's Landsat satellite imagery at 30-meter resolution, we conducted an LULC change detection using data from 2010, 2014, 2017, and 2020. We first provide a full accounting of forest loss and expansion of other land cover types following the camp openings. Our descriptive analysis reveals forest cover reductions and settlement expansion across Cox's Bazaar since 2010. More recently, forests declined by nearly 20 percent from 2017 to 2020, while settlements expanded by 21 percent between 2017 and 2020.

Across the district of Cox's Bazar, we use a stratified random sampling method to select 10,000 points and build a spatially explicit pixel-year panel data set that identifies the geodesic distance between each point and the nearest camp (in kilometers), as well as each point's land cover class by year. Based on our initial descriptive analysis, we designate pixels 0-5 km from the nearest camp as part of the "treatment" group and pixels 10-15 km from the nearest camp as "control." Using a difference-in-difference framework that includes year and pixel fixed effects, we find evidence of significant forest loss 0-5 kilometers from camp boundaries. All else equal, we find that pixels within this distance buffer were 7.6 percentage points more likely to become deforested relative to the control area after camp openings. Our heterogeneity analysis suggests that these forest losses are concentrated outside protected natural areas. Moreover, we find that settlement areas are expanding faster in the 0-5 km buffer area relative to control: pixels within the treatment buffer were 13 percentage points more likely to convert to settlement after camp openings.

2. Literature Review

Why might refugee camps trigger forest cover losses? The arrival of thousands of displaced people constitutes a sudden and large increase in the local population count. Population growth has the potential to drive forest loss because of the resulting increase in the area needed for shelter and for agriculture, which (in the absence of appropriate technologies) requires an expansion in agricultural land use, often at the expense of forests.

There are other reasons why refugee camps can trigger forest cover loss. Evidence from Kakuma Camp in Kenya shows that camps can stimulate economic activity (Alix-Garcia et al., 2018). This is partly because refugees often participate in local markets. They expand the local supply of certain goods when they sell portions of their in-kind aid package. They also influence demand when they draw on savings, remittances, credit, and (in some cases) income to make purchases (Betts, Bloom, Kaplan, & Omata, 2017). If camps stimulate additional market activity at the outskirts of the camp, then this activity may lead to forest cover loss.

Another potential mechanism is in-migration. Multilateral agencies and donor governments financially supporting refugee camps are increasingly allocating aid towards host communities to offset some of the negative externalities of hosting. Increased aid receipt for hosts living near camps may trigger selective in-migration, leading to land clearing for new inhabitants. Additionally, if refugee camp construction and management are labor-intensive, and if refugees are prohibited from income-generating activities, then a camp may provide additional work opportunities for non-refugees, which may also induce in-migration. To the best of our knowledge, there are no prior studies that consider whether refugee camps stimulate in-migration. Related studies on aid receipt in developing countries and international migration offer mixed results, with some evidence that more aid for rural communities reduces the likelihood of those communities seeking employment abroad (Gamso & Yuldashev, 2018).

There are several prior efforts using remote sensing to capture forest loss around camps in Cox's Bazar, Bangladesh (Hassan et al., 2018; Tani and Rahman, 2018; Hossen, Hossain and Uddin, 2019). These studies provide analyses of land-use changes, but they mainly rely on a first-differences framework that cannot account for endogenous differences between camp and non-camp areas or the forest losses that would have occurred in the absence of the 2017 refugee arrival.

The causes listed so far are tied to sudden population growth or sudden augmentations in aid receipt. But for over three decades, scholars have also wondered whether the experience of forced displacement leads people to degrade landscapes more than other groups.[4] Those who support this theory argue that refugees are "exceptional resource degraders" because of several factors specific to forced displacement. Firstly, it has been argued that refugees and migrants have an "expansionist attitude" towards land-use and natural resource exploitation given their weak socio-cultural ties to the natural landscape. Moreover, studies suggest that poorer members of society disproportionately depend on the environment for sustenance more than those who are better-off (Broad, 1994). Hence, if refugees are more impoverished than their host population, perhaps they could be more dependent on natural resources. Others think that because refugees may not be invested in staying they will have a "short time horizon" and thus may be more

[4] For a thorough overview of the literature and debate on refugees as "exceptional resource degraders", see Black (1998).

aggressive in their resource use than their host counterparts (Leach, 1992; Codjoe, 2006; Codjoe & Bilsborrow, 2012; Jacobsen, 1997; Rahman, 2017).

But several scholars have cast doubts on the exceptional resource degraders hypothesis (Black, 1998; Black & Sessay, 1997; Kibreab, 1997). Kibreab (1997) argues that refugees often live alongside poor host communities who also depend on natural capital from forests to smooth consumption and obtain goods. Moreover, the lack of security with respect to land tenure is common in many poor countries, meaning refugees may not be so "exceptional" in this regard. Another possibility is that refugees extract *less* from the forests than hosts, given the fact that in many countries their mobility outside of camp areas is restricted.

The exceptional resource degradation claim has proven weak in case studies where refugees and migrants are socially and economically integrated. Integrated refugee populations are less likely to rely heavily on natural resources, more likely to find alternative sources of income and livelihood strategies, more likely to get assistance from members of their host communities, and more likely to comply with local rules and regulations due to social pressure (Cassels, Curran, & Kramer, 2005; Codjoe & Bilsborrow, 2012). Similarly, co-management of natural resources between the local communities and their governments, reinforced with increased enforcement of environmental regulations, could further deter the overexploitation of natural resources (Dampha, 2020; Ostrom & Cox, 2010). Hence, including refugees in the sustainable management of land and forest resources may yield positive environmental outcomes.

Overall, the empirical findings on the exceptional resource degraders' hypothesis are mixed and dependent on the institutional and policy context in various places. For instance, in the Senegal River Valley, Black and Sessay (1998) found little or no evidence that refugees used more wood fuel than their host community counterparts. The study concluded that both refugees and host community members pursued similar livelihoods strategies. Black and Sessay (1998) also found no evidence that refugees in the area do not respect and comply with the local environmental management and protection rules and regulations. Furthermore, using *land extensification* (cultivation of new land and tractor use) and *land intensification* (fallow time in the previous five years and fertilizer) as measures of degradation, Codjoe & Bilsborrow (2012) found no evidence supporting the claim that migrant households engage in more land extensification than the host community. However, in terms of land intensification, the evidence supports the hypothesis that households with migrants fail to allow more land to fallow than the host population.

3. Background

3.1 Cox’s Bazar, Bangladesh

Our study area, Cox’s Bazar, is a district in the Chittagong Division situated in Bangladesh’s southeastern corner (Figure 1) between the River Naf to the east and the Bay of Bengal to the west and south (Hassan et al., 2018). The study area has a total land area of 213,639 ha (2136.39 km2). The area is elongated in shape, stretching about 135km in the north-south direction and 30km in the east-west direction– from the upper northern part, narrowing down to less than 3km around the lower southern part.

Cox’s Bazar is home to an estimated 2.7 million Bangladeshis. The majority of the residents depend on natural capital assets and ecosystem services derived from agriculture, forests, marine and cultured fisheries resources, and eco-tourism services for their livelihoods (Tallis et al., 2019; Tani & Rahman, 2018). A study before the 2017 refugee influx shows that 57 percent of households, including their refugee counterparts in the region, “totally depend on forests” for their livelihoods (Uddin & Khan, 2007). According to the Bangladesh Bureau of Statistics, about 63 percent of the area’s total population is involved in the agriculture sector, 25 percent engaged in the service sector, and about 12 percent employed in the industry sector (Hassan et al., 2018). Several studies have indicated the involvement of many of these residents in crop production at subsistence level, betel leaf and betel nut gardening, salt extraction, fuelwood production, as well as capture and cultured fisheries production (Hassan et al., 2018; Mukul et al., 2019; Tallis et al., 2019; Tani & Rahman, 2018; UNDP & UN Women, 2018).

The study area falls under a subtropical climate characterized by different seasonal variations with relatively high temperatures (average 78.98 ◦F (26.1 ◦C)/year) and receiving significant precipitation events (average rainfall estimated at 4,000 mm/year). The four most common seasons known to the area are a hot-humid summer/pre-monsoon season (March to May), a cool-rainy monsoon season (June to September), a cool-dry winter/post-monsoon season (October to November), and the dry season (December to February) (Hassan et al., 2018; Tani & Rahman, 2018; UNDP & UN Women, 2018).

Cox’s Bazar is mostly floodplain (Alam, Huq, and Rashid, 1999) with a mean slope of 4 degrees and a mean elevation of 17 meters above global mean sea level (MSL). The area’s geomorphological features include flat floodplains, mudflats, dunes, tidal creeks, hillocks, and sandy beaches stretching 120 km along the Bay area (Alam et al., 1999; Hassan et al., 2018). Cox's Bazar Sea beach is described as one of the most popular destinations for tourism in Bangladesh (Hassan et al., 2018; Hassan & Shahnewaz, 2014).

The landscape in this district is predominantly known for its dense forested areas, including protected areas, nature reserves, and national parks (Hassan et al., 2018; UNDP & UN Women, 2018). More than 25 percent of the district has forest cover of some sort, of which an estimated 10,849 ha is under the protected forest status (Hossen et al., 2019), and 11,615 ha is a designated wildlife sanctuary (e.g., Teknaf Wildlife Sanctuary) (UNDP & UN Women, 2018). The forest ecosystem is also home to thousands of plant and animal species, such as birds, monkeys, snakes, bats, among other vertebrate and invertebrate species. It also includes threatened and critically endangered species, such as the wild Asian elephant (Hassan et al., 2018; Tallis et al., 2019; UNDP & UN Women, 2018).

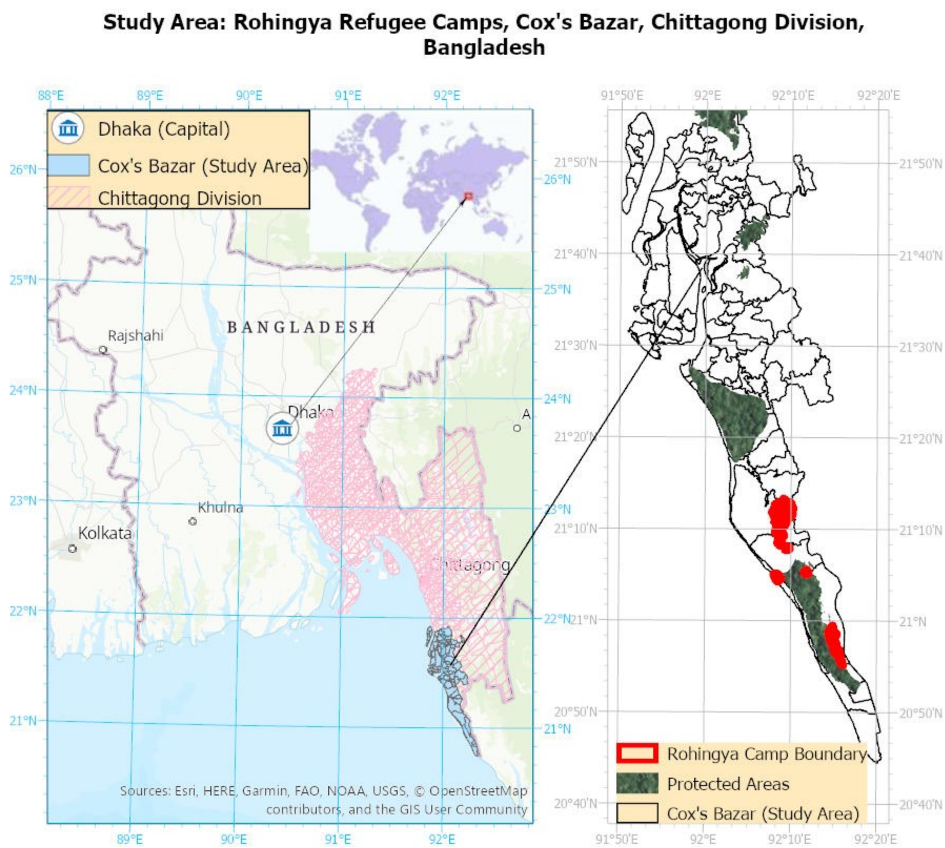


Figure 1: Study Area Showing the Geographic Location of Rohingya Refugee Camps, situated in Cox's Bazar District, Chittagong Division, Bangladesh.

3.2 Rohingya Refugees

The Rohingya people are a Muslim ethnic minority group indigenous to the territories of the historic Arakan region, which today corresponds with the Rahkine State of Myanmar (formerly known as Burma). The recent era of Rohingya displacement to Bangladesh began in the 1970s. Shortly after the Burmese military assumed full power over the country in 1962, the regime began to strip Rohingya peoples of their citizenship and cast them as outsiders or "illegal immigrants." Secondary accounts often emphasize acute periods of violence against the Rohingya people in 1978 and 1991-1992. In both episodes, tens of thousands of Rohingya refugees were forced to seek asylum in Cox's Bazar (Ullah, 2011). While these moments of large population displacement garner considerable attention, smaller-scale displacement of Rohingya asylum-seekers to Bangladesh has also occurred rather continuously over time, with steady movements of households seeking refuge from violence, persecution, extortion, and forced labor at the hands of the Burmese military or extremist groups (Human Rights Watch, 2000; Ibrahim, 2016).

It is difficult to estimate the population size of the Rohingya refugees in Cox's Bazar at the eve of the 2017 influx. Many of those who fled to Bangladesh in earlier years were repatriated to Myanmar, in some cases only to be displaced again when conditions worsened (Ullah, 2011). From Bangladesh, others fled to southeast Asia by sea (Aung, Sumarlan, Hayes, & Rahman, 2016). Moreover, not all of the Rohingya asylum-seekers registered as refugees, which means they were not included in official UNHCR population counts. It is generally believed that about 200,000-300,000 Rohingya refugees resided in Cox's Bazar - either in camps or in host communities - shortly before the 2017 population influx (Pamini, Othman, & Ghazali, 2013; Tay et al., 2018).

Our paper focuses on the impact of the most recent large population influx from Rakhine State to Cox's Bazar. In 2017, an estimated 6,700 Rohingya were killed in a conflict that erupted between the Arakan Rohingya Salvation Army (ARSA) and the Myanmar Military (Gee, 2017; Labib et al., 2018). Given the scale of the violence against Rohingya non-combatants and the "scorched Earth" nature of the military's brutal campaign, hundreds of thousands were forced to flee their homes and cross the border into Cox's Bazar. This most recent period of violence has led numerous multilateral groups to accuse Myanmar of ethnic cleansing, genocide, and crimes against humanity.[5]

An estimated 726,221 Rohingya refugees arrived in Cox's Bazar between August and December 2017. By UNHCR's estimates, this resulted in an increase in the total Rohingya population in Bangladesh to nearly a million people (884,041 registered refugees living in the Cox's Bazar district) of which 96 percent arrived since 2016 (UNHCR, 2021). The Government of Bangladesh, with the support of UNHCR, built many new camps in the Cox's Bazar area to accommodate the newly arrived Rohingya refugees. Today, the district houses the largest population of refugees anywhere in the world. The Kutupalong–Balukhali camp expansion site alone has a total of 603,315 residents. The majority of the refugees are encamped in hilly areas, which were previously forested, vulnerable to landslides, and highly exposed to cyclones and flash flooding due to extreme precipitation events during the cool-rainy monsoon season (Arfin Khan, Uddin, and Haque, 2012; Milton et al., 2017; Rahman, 2017; Hassan et al., 2018; Labib, Hossain and Patwary, 2018; UNDP Bangladesh and UN WOMEN Bangladesh, 2018; BBC News, 2020).

The Rohingya refugee population in Cox's Bazar is young, unemployed, and has limited access to educational opportunities. An estimated 53 percent of the total population are children, and 34 percent have no formal education. The Rohingyas' top-five household priority needs include food, materials for upgrading shelters, electricity for improving safety at night, clean drinking water, and fuel for cooking. To reduce pressure on nearby forests and improve Rohingyas' health and well-being in the refugee camps, the UNHCR and partners initiated the distribution of liquefied petroleum gas (LPG) cylinders to refugees and later to some host community households. In August of 2018, the pilot program supplied LPG cylinders to only some of the refugee households. When scaled-up in February of 2019, about 1,242,995 LPG cylinders (1st time + Refill) were distributed to Rohingya households as of 2020, in addition to 46,694 LPG cylinders delivered to host community households in Cox's Bazar (UNHCR, 2020b). In 2019, 75 percent of Rohingya households had reported using the UNHCR's provided

[5] For instance, during the violent displacement of Rohingya refugees in late 2017, UN High Commissioner for Human Rights Zeid Ra'ad al-Hussein called the case a "textbook example of ethnic cleansing" (Nebehay, 2017). And in November 2019, the Republic of The Gambia filed a case against the Republic of the Union of Myanmar before the International Court of Justice, "alleging violations of the Convention on the Prevention and Punishment of the Crime of Genocide (the "Genocide Convention") through acts adopted, taken and condoned by the Government of Myanmar against members of the Rohingya group" (International Court of Justice, 2019, p.1).

LPG cylinders for cooking (Inter-Sector Coordination Group, 2019). The LPG program has reduced refugees' dependence on forests for fuelwood extraction. However, there is still an increasing demand for bamboo extraction (a forest product) for shelter construction. According to local sources, bamboo for refugee shelters is predominantly sourced from the nearby Chittagong region, but is now also supplied from other regions in Bangladesh.

Although Rohingya refugees in Cox's Bazar benefitted from relatively unconstrained mobility prior to 2017, the recent population influx has led the Government of Bangladesh to impose stricter policies regarding refugee movements. Presently, the Rohingya refugees are compelled to stay in the camps, a policy that has become increasingly enforced with the introduction of fencing and road checkpoints. They are also denied access to public facilities, including access to school, and are not allowed to seek employment to generate income (Tani & Rahman, 2018). Consequently, an overwhelming majority (73 percent) of Rohingya refugees reported having "no interaction" with members of the host communities, according to a 2019 survey report. Among those who interact, 17 percent was casual interaction, and only 1 percent was work-related interactions (Inter-Sector Coordination Group, 2019).

However, a recent study highlighted rapid growth in business activities in Cox's Bazar since the 2017 arrival of forcibly displaced Rohingyas. The study concluded that both local Bangladeshis and Rohingya refugees have access to a diverse variety of well-functioning businesses inside and outside (only for Rohingya with legal work permit) the camps, including trade, services, manufacturing, among others. They also found increasing evidence of "business-to-business and business-to-customer interactions between the owners, suppliers, workers, and clients of both Rohingya and Bangladeshi communities" (Filipski, Rosenbach, Tiburcio, Dorosh, & Hoddinott, 2020).

4. Data

4.1 Geospatial Data

This analysis primarily uses remotely sensed data/images captured by the Landsat satellite, operated by the US Geological Survey (USGS).[6] The image selection considers potential

[6] We present details on the data sources and descriptions in the Appendix A1.4. To obtain this table please contact the corresponding author.

atmospheric distortions and similar temporal resolution for all selected periods. We downloaded images (30-meter spatial resolution) with less than 10 percent of cloud cover from mid-to-late-February for all years falling within Bangladesh's dry season. Although data from the European Space Agency's Copernicus satellite, Sentinel-2 A/B offers better spatial resolution (10 meters), we did not use it because of lack of availability in earlier years (before 2014).

We used additional geospatial data. First, we use Protected Planet's World Database of Protected Areas map to classify areas of Cox's Bazar as wildlife refuges, national parks, or non-protected (UNEP-WCMC & IUCN, 2021). We also use annual population data (2010-2020) derived from the Worldpop Population Counts unconstrained, UN-adjusted maps at 100m resolution (Lloyd et al., 2019). For estimates of economic productivity, we use the VIIRS 2014-2020 Nighttime Lights data produced by NOAA. This data has a spatial resolution of 15 arc-seconds and is collected monthly. We derive annual estimates of nighttime lights by averaging across months.[7] Finally, we gauge remoteness using the Google Maps API and its static maps of main road locations.

To construct our data set, we draw a random sample of 10,000 pixels across the district and derive zonal statistics of the pixel's land cover classes for 2010, 2014, 2017, and 2020, the annual population of the 100m grid the pixel falls in (2010-2020), and the nighttime lights score for the pixel (2014-2020). We also determine static characteristics, including whether the pixel is in a protected area, the pixel's geodesic distance[8] to the nearest border of a camp that opened after Rohingyas arrived in 2017, and the pixel's geodesic distance to the nearest main road.

4.3 Image Processing

For the image preprocessing, we use some of the in-build radiometric enhancement techniques in ArcGIS pro to improve the quality of data visualization during image processing. These techniques enhance our ability to interpret the image correctly. For instance, we use the Normalized Difference Vegetation Index (NDVI), a spectral enhancement technique, to

[7] Elvidge, Baugh, Zhizhin, & Hsu (2013) argue that VIIRS better captures nighttime lights as compared to the DMSP maps. Hence, we opt for VIIRS over DMSP for this study.

[8] A geodesic distance measures the shortest path between two points on a curved surface, like the Earth (ESRI, 2021).

transform and manipulate data structure to maximize data display for vegetation cover detection (Tammy, McGee, and Campbell, 2019). Vegetation cover here refers to all green spaces, including forests and agricultural plots within the study area. The NDVI is widely used to monitor vegetation change dynamics from local, regional to global scales and has been shown to be a useful measure of vegetative land cover change (Hassan et al., 2018). The NDVI is calculated as:

$$\text{NDVI} = \frac{(\text{NIR}-\text{Red})}{(\text{NIR}+\text{Red})}$$

where NIR is near-infrared light and Red is the visible red light of the satellite's electromagnetic spectrum. Bearing in mind the sensitivity of vegetation health to the broader climatic and local weather conditions in Cox's Bazar area, Hassan et al. (2018) generated NDVI data using images captured only in the dry season months, including February. We also added the NDVI analysis to show vegetation health and green cover changes in the study area. The NDVI can detect vegetation cover change between mass pre-refugee arrivals in 2017 relative to post-arrival for areas within and without of current refugee camp boundaries. The higher the NDVI value, the healthier the vegetation cover.[9]

We have identified some image post-processing issues to be considered when interpreting our results below. First, we observed that areas classified as "bare ground" in locations farther away from settlements are "cleared farmlands" usually visible in a post-harvest period in the study area. Thus, cleared farmlands contribute to an increase in empty ground areas, as reported in Table 2. As cultivated areas increased in any given year, perhaps, due to late-harvest, bare ground sites decreased, and vice versa. Second, due to hydrological dynamics (i.e., surface water appearances and flows), we combined the water body areas with cultured fisheries sites into a single class for simplification in Table 2.

Given that this geospatial analysis is interested in a change in forest cover, we are less concerned about the potential classification errors among the other classes, which can be attributed to our data's coarse spatial and spectral resolution issues. However, we are highly

[9] Very low NDVI values (0.1 and below) represent bare ground areas of rock, sand, or snow. Moderate values (0.2 to 0.3) correspond to shrub and grassland areas, and high values (0.6 to 0.8) indicate temperate and tropical rainforest covers (Weier & Herring, 2020).

confident about the accuracy of the LULC types classified as forests and settlements. Forest cover, as used in this study, refers to dense, moderate, and sparsely forested areas as well as woodlands, grasslands, shrublands, orchards, and fruit trees within the study area. The spectral characteristics of areas shown as forests, including grassland and other forest cover types, are quite different from other LULC types' spectral features. Similarly, as presented below, the NDVI results also validate our confidence level in forest area classification.

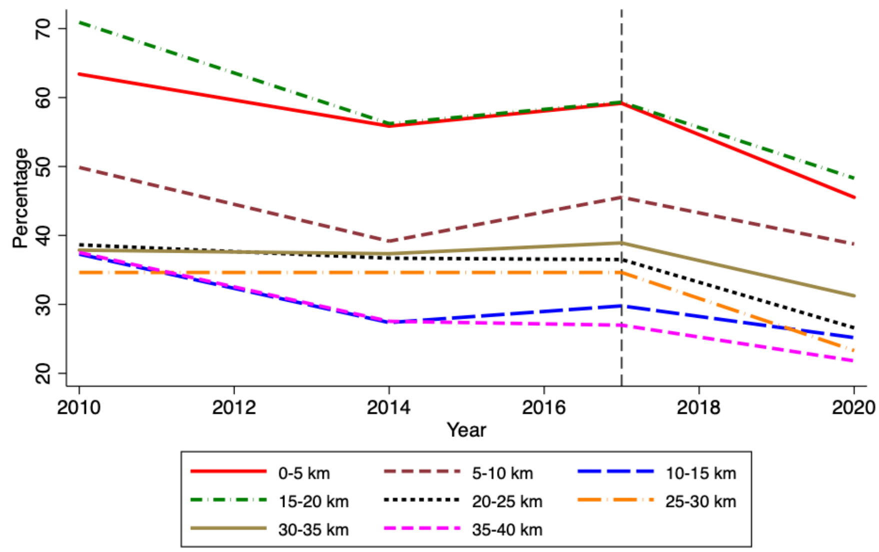
4.4 Panel Data Construction and Descriptive Figures

We generate a random data set of 10,000 pixels across Cox's Bazar. With our LULC classified maps and other GIS inputs (Section 2.1), we derive zonal statistics for each pixel. We use this initial sample to determine an analytical approach that allows us to estimate a valid counterfactual scenario and hence account for land cover changes that would have taken place in the absence of the large population influx. This is especially important since camp locations are not randomly determined (Maystadt & Verwimp, 2014) and since we observe considerable deforestation across the district in earlier years.

Figure ***2*** provides the percentage of pixels classified as forest in our sample by year and distance to the nearest refugee camp border. Prior to camp construction in late 2017, pixels 0-5 km from the nearest camp tended to be heavily forested. To a large extent, this is because several of the camps sit on the border of the Teknaf Wildlife Preserve, a highly forested area (see Figure 1). We also observe high forest cover 15-20 km away: at this distance, many pixels fall within Himchari National Park. Pixels that are 5-15 km from the nearest camp, or 20-40 km from the nearest camp, tend to have lower forest cover on average. From 2010 to 2020, the time series shows a steady decline in forest cover in all the distance buffers.

There appears to be a small rise in forest cover between 2014 and 2017, which is surprising given the overall trend to less forest cover in the region. Key informants involved in environmental management in Cox's Bazar have pointed out that forests in the district can recover relatively quickly. The World Bank also funded participatory reforestation and afforestation efforts in the district between 2013 and 2016, which could explain this marginal increase in forest cover between 2014 and 2017 (Arrannayk Foundation, 2017). But without more information, we also acknowledge that the 2014 land-use classification may under-estimate forest cover for that year. As long as the measurement error in the dependent variable is random, however, it should not bias our econometric estimates (Wooldridge, 2010). But such measurement error would bias our descriptive estimates of forest losses over time.

Figure 2: Forested pixels by year and distance to nearest refugee camp border (percentage)



Source: authors' calculations using land cover classified maps produced from Landsat remote sensing imagery.

Although they reflect different levels of forest cover overall, we selected the 0-5 km buffer as our treatment area and used the 10-15 km buffer as our control area, as these visually exhibit parallel trends prior to the camps being established. We do not expect refugees to be traveling over 10 km from the camp boundaries because, as mentioned in Section 2, Rohingya refugees face mobility restrictions and rarely interact with hosts. This spatially explicit treatment and control pairing can help us determine the impacts of the camps. But we do not believe that all camp-stimulated changes take place within close proximity of camp borders. For example, increased food demand may drive local agricultural expansion, but this need not occur adjacent to the camps, given decent road access.

Table 1 provides descriptive statistics for the treatment and control areas evaluated for this study. The land cover characteristics of these areas in any given year are dissimilar: the control area exhibits higher agricultural land-use and settlement cover over time, while the treatment buffer tends to have greater forest cover and bare ground cover. Despite these differences, so long as parallel trends hold, we can still estimate a reasonable counterfactual for the treatment area using the control area's trends. The control area also shows signs of higher human activity before the creation of the camps. The mean nightlights score and average population tend to be higher, and the average distance to the nearest main road tends to be lower. In both treated and control areas, about 30 percent of the pixels fall in a protected area.

Table 1: Descriptive statistics by treatment status and year

	2010		2014		2017		2020	
	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control
Percent water	3.90	0.48	2.25	0.73	1.99	4.12	1.72	0.73
Percent settlement	18.40	44.07	22.04	52.54	20.78	46.97	35.08	49.39
Percent bare ground	7.41	7.26	10.32	8.72	7.88	4.36	7.48	3.15
Percent forest	63.40	37.29	55.86	27.36	59.17	29.78	45.53	25.18
Percent aquaculture	0.60	1.45	3.18	4.36	0.40	1.69	0.33	3.87
Percent agriculture	6.29	9.44	6.35	6.30	9.79	13.08	9.86	17.68
Mean lights index	-	-	0.13	0.33	0.31	0.59	0.49	0.71
Mean population	5.26	8.35	5.68	9.34	6.06	10.10	6.22	11.04
Percent national park	0.00	29.06	-	-	-	-	-	-
Percent wildlife preserve	29.38	0.00	-	-	-	-	-	-
Mean distance to road (km)	0.29	0.11	-	-	-	-	-	-
Observations	1,511	413	1,511	413	1,511	413	1,511	413

Source: authors' calculations based on a random sample of pixels in the Cox's Bazar district. For each pixel, we determine land-use / land cover (LULC) classified maps using Landsat remote sensing imagery for the district in the years 2010, 2014, 2017, and 2020. We determine the population using Worldpop unconstrained individual country and UN adjusted data for 2010-2020. The night lights score for each pixel comes from the VIIRS Night Lights Index data for 2014-2020. Static statistics only appear in the first and second columns. The classification of pixels into national parks and wildlife preserves comes from Protected Planet's World Database of Protected Areas map. We derive the pixel's geodesic distance to the nearest main road using the Google Maps API. The distance buffer, which we use to assign pixels to treatment and control groups, is determined by the pixel's minimum geodesic distance to the nearest camp border. Treated pixels are 0-5 km from the nearest camp, and control pixels are 10-15 km from the nearest camp

5. Methodology

5.1 Geospatial Analysis

In this analysis, our land-use / land cover (LULC) classification problem was to identify six land-use/ land cover (LULC) types: forests, settlement/developed, cultivated/agricultural areas, cultured fisheries ponds, bare ground, and surface water for all selected years, 2010, 2014, 2017, and 2020. The geospatial analysis was carried out using the ArcGIS Pro software (Version 2.4.0, 2019) for image classification and map visualization. We used a pixel-based supervised classification method for image processing.[10] To execute the classification, three different algorithms, namely random forest (RF), maximum likelihood estimation (MLE), and support vector machine (SVM), were tested and compared to consider their relative accuracy. In this analysis, the random forest (RF)[11] produces a relatively better result than MLE and SVM. Using the image values of land cover maps created using the RF algorithm, we calculated the aggregate change for various LULC types between the periods 2010, 2014, 2017, and 2020 (Table ***2***).

5.2 Econometric Analysis

Our econometric analysis uses a linear probability model with a difference-in-differences framework to capture changes in land cover trends in response to camp openings. We focus on pixels 0-5 km from the nearest camp because we expect these pixels to be the most exposed to refugee activity as well as any camp-related changes in economic activity. As discussed in the previous section, we assign pixels 10-15 km from the nearest camp to the control group. We estimate the following regression:

$$\Pr(y_{it}^{c} = 1) = \alpha + \beta(treated_i * after_t) + \gamma_t + \rho_i + u_{it} \tag{1}$$

[10] A schematic model of the step-by-step GIS-based analysis is shown in Appendix A1.3 (contact author).

[11] The RF algorithm, a nonparametric machine learning classifier, has widespread application in remote sensing because of its high classification accuracy, insensitivity to noise, ability to handle overtraining effects (Breiman, 1999; Pal, 2005; Chan and Paelinckx, 2008; Ghimire, Rogan and Miller, 2010), capability to determine variable importance (Rodriguez-Galiano et al., 2012), and because it requires fewer user-defined parameters compared to SVM (Pal, 2005).

where y_{it}^{c} is a binary indicator of whether pixel i belonged to land cover class c in year t, γ_t is a fixed effect for year t, ρ_i is a fixed effect for pixel i, and u_{it} is an error term.

We also examine three other LULC classes: settlement, bare ground, and agriculture. We focus on these particular land cover types because of their relevance to understanding the potential impacts of camps on forest loss. An expansion of bare ground areas would suggest that camp residents are clearing land as they extract fuelwood. Settlement expansion would suggest that Bangladeshis are moving towards the camps in pursuit of economic opportunities or improved access to services. Agricultural expansion would speak to increased demand for local food after a sudden population increase. As mentioned, our LULC classification results in a "medium classification accuracy" concern between bare ground and cultivated land so we do not have complete confidence in being able to distinguish between clearing land for wood collection versus clearing land for agricultural expansion. Moreover, agricultural expansion need not take place at the immediate outskirts of camps given sufficient road access. But as mentioned previously, we are confident in our ability to identify settlements as well as forests from other land cover types.

With the inclusion of time and pixel fixed effects, we do not need to separately control for whether the time period is after treatment or whether the pixel is treated. The pixel fixed effect accounts for a variety of time-invariant characteristics important for our study, such as soil fertility, whether the pixel is in a protected environmental area, and steepness of the slope. Given the small geographic scope of this study, or time fixed effect controls for seasonal variations that we expect to be relatively homogeneous across the district, such as annual rainfall. Our coefficient of interest is $\beta,$ which tells us the change in forest cover after camp opening for treated pixels relative to a counterfactual estimate based on the control area's trends. Because there is no clear group structure to our observations (Cameron & Miller, 2014) and because we are not doing two-stage sampling (Abadie, Athey, Imbens, & Wooldridge, 2017), we do not cluster our standard errors.

To provide greater confidence that parallel trends hold, we drop 2020 (post-treatment) observations and re-estimate Regression 1, first using 2014 as a placebo first year of treatment, then using 2017 as a placebo year. If the coefficient of interest is insignificant in these specifications, then we are more confident in parallel trends prior to Rohingya's arrival. If the coefficient of interest is significant, then we suspect that trends deviated prior to treatment.

To more closely examine whether camps attract in-migration and the expansion of economic productivity, we examine population and nightlights as outcome variables in the regression:

$$y_{it} = \omega + \kappa(treated_i * after_t) + \mu_t + \delta_i + \epsilon_{it} \quad (2)$$

Regression 2 is identical to Regression 1, but the outcome variable is continuous. We examine two dependent variables: the natural log of the population in the 100m tile the pixel falls in[12] (using annual data 2010-2020), and the nighttime lights score for the pixel (using annual data 2014-2020). Like with Regression 1, we adjust Regression 2 so that we can test for parallel trends. After dropping observations from 2017 or later, we test two treatment year placebos in separate regressions: one assigning 2015 as the placebo treatment year, and one treating 2016 as the placebo treatment year.

5.3 Robustness Check

It is plausible that changes outside the camp's official boundaries may be due to unofficial camp expansion. Prior to the construction of fencing, camp residents may have expanded their settlement areas beyond the demarcated border of the camp in order to alleviate population pressure. To ensure that any changes in the treatment area are not due to unofficial camp expansion, we conduct a robustness test in which we repeat Equation 1, omitting all pixels 0-1 km from the camp boundary.

5.4 Heterogeneity Analysis

Some of the camps sit alongside the Teknaf Wildlife Preserve. Given the importance of protecting this area's forest cover and biodiversity, we conduct a heterogeneity analysis to see if pixels in protected areas are deforesting more or less than pixels in non-protected areas. To do so, we repeat Equation 1 for the sub-sample of treatment and control pixels in protected areas and additionally repeat the regression using only treatment and control pixels outside protected areas.

[12] None of the sample pixels has an estimated population of zero. Hence, a natural log transformation will not induce bias but will facilitate the interpretation of the coefficient estimate.

6. Result

6.1 Descriptive Results

We observed a decrease in forest area since 2010 in the study region (Table 2). Forest cover loss has accelerated since 2017 compared to earlier years. Forest cover declined by nearly 20 percent between 2017 (pre-arrival) and 2020 (post-arrival) across the entire district, corresponding to an annual loss of 6.7 percent. Forest cover reduction is associated with an increase in settlement areas across the district (Figure 3, Figure 4). In 2020, settlement areas increased by 21 percent relative to the 2017 estimate (pre-arrival) period.

Table 2: Descriptive land cover changes across all of Cox's Bazar, 2010-2020

	2020	***2020-2017***	***2017-2014***	***2014-2010***
Class Name	Share of Total Land Area ha (%)	Net change (ha) (% Change)	Net change (ha) (% Change)	Net change (ha) (% Change)
Forests/ grassland	52629 (25%)	-12807.99 (-19.57)	-135.99 (-0.21)	-3663.99 (-5.59)
Water/ Fish-ponds	39875 (19%)	-2272.50 (-5.39)	1367.46 (3.35)	3249.99 (8.66)
Developed/ Settlements	82631 (39%)	14511.42 (21.30)	4028.76 (6.29)	-192.06 (-0.30)
Barren/ Bare grounds	12202 (6%)	1757.07 (16.82)	-980.01 (-8.58)	3447.81 (30.18)
Planted / Cultivated	26302 (12%)	-1201.50 (-4.37)	-4280.22 (-13.47)	-2841.75 (-8.94)

Note: The 2020 column shows the share of the total area in ha. The brackets are percentage areas for each class. The rest of the columns shows the net change between the two periods in hectares and percentage changes in the bracket.

We find strong evidence of LULC change from forests to settlements within the areas identified as current refugee camps. The official refugee camps occupied a total land area of 2,545 ha. Before the Rohingya influx in February 2017, 54 percent of the existing campsites were forested compared to only 2 percent in 2020 (post-arrival), which corresponds to a forest cover loss of 1,337 ha (Figure 4). The NDVI map visualizes the study area's vegetation condition over the past three decades, reflecting that the most vegetation cover change occurs in the post-arrival period following the 2017 Rohingya influx (Figure 5). The mean NDVI value within the camp areas declined by 98 percent when the pre-arrival era (February 2017) is compared to the post-arrival period (February 2020). There has been a loss of forest cover or green spaces within and around the official refugee camp boundaries whether one relies on this study's LULC classification estimates or the NDVI results (Appendix A1.1-2).[13]

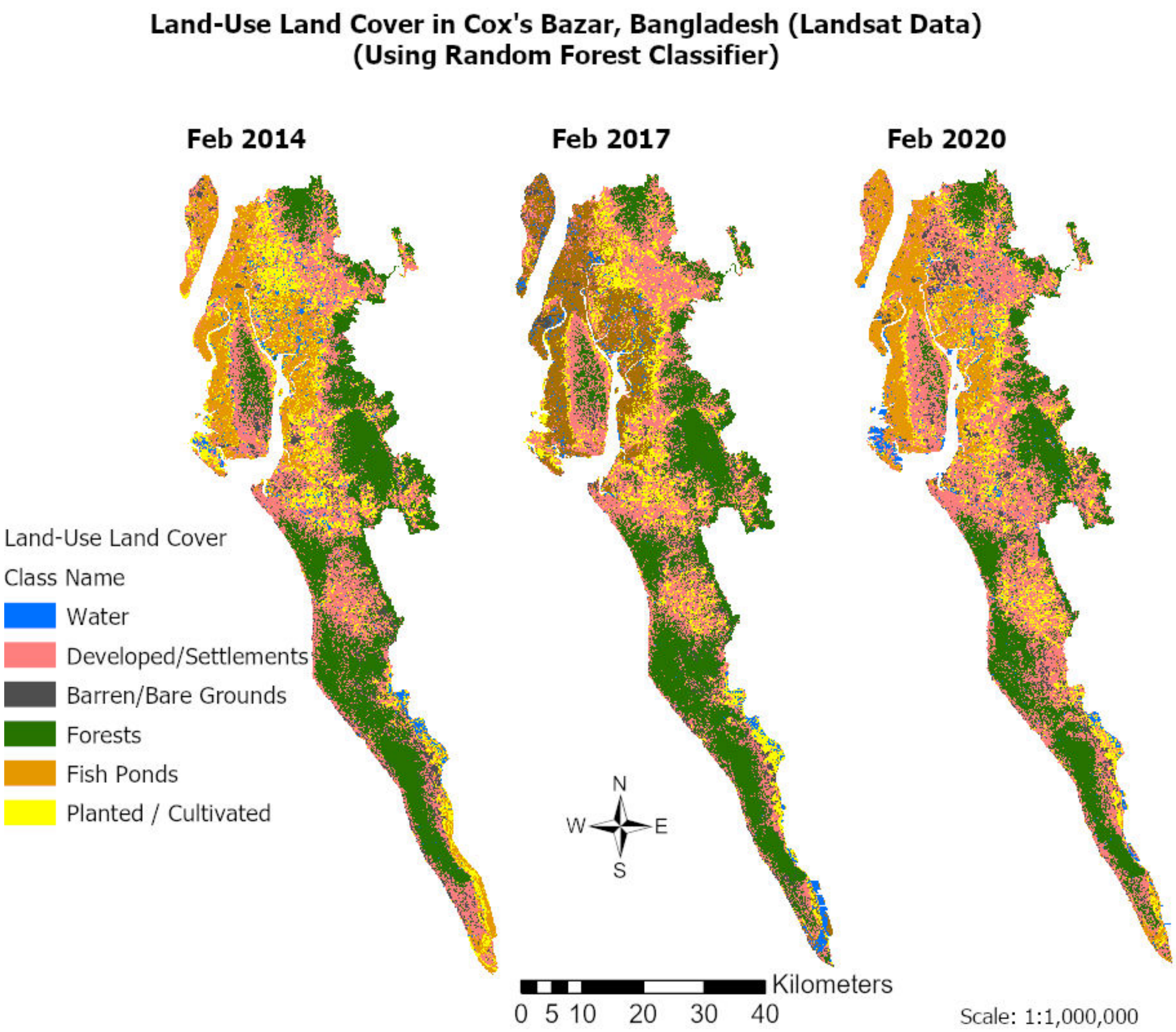


Figure 3: LULC Composition of our study area, Cox's Bazar, Bangladesh, using a small-scale map. The maps show how the 2014 and 2017 pre-arrival periods differ visually (at a small scale) from the LULC composition of the area in 2020, post-arrival of Rohingya Refugees.

[13] To obtain the appendix, please contact the corresponding author.

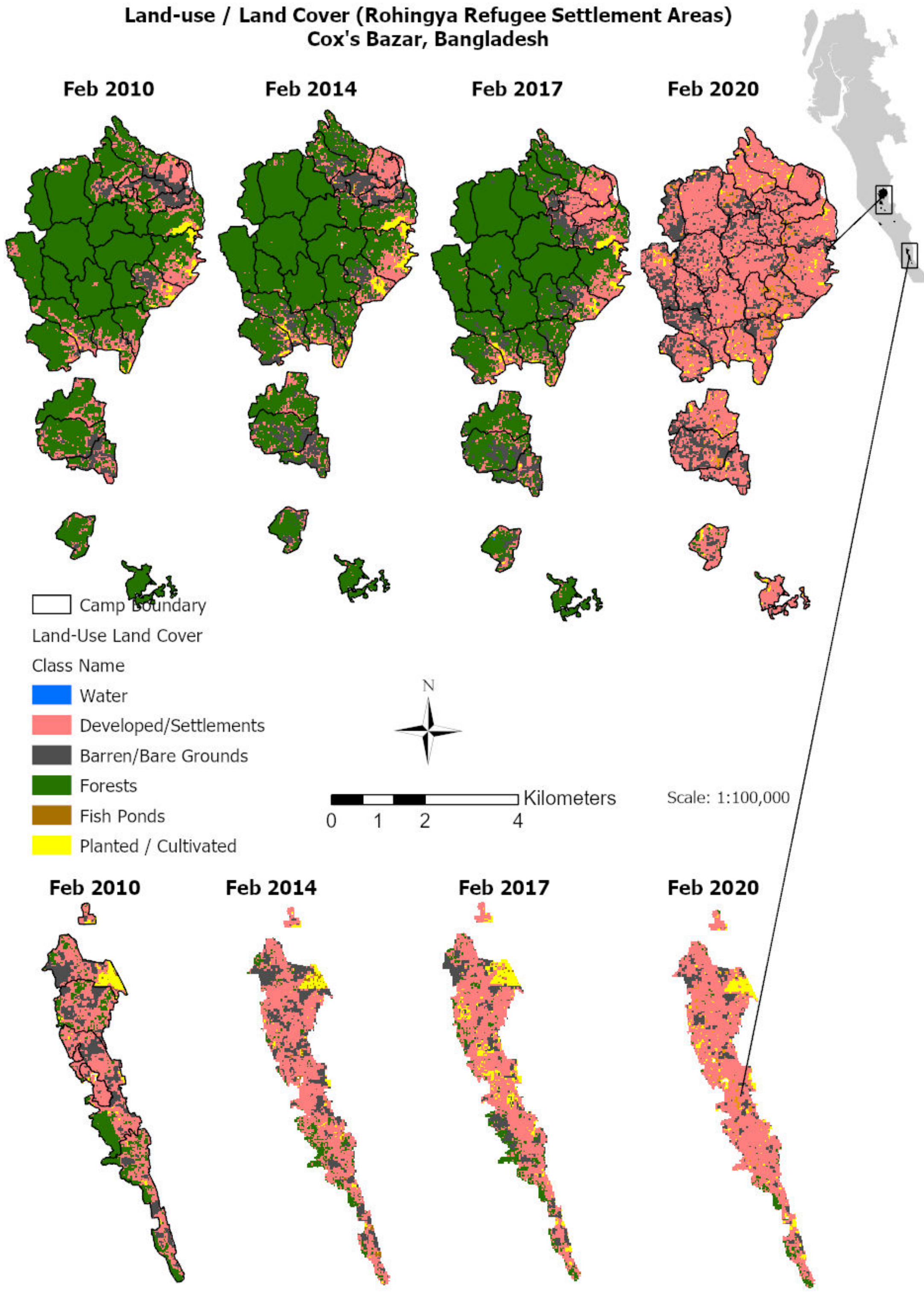


Figure 4: LULC Composition of the Current Rohingya Refugees Campsites in Cox's Bazar, Bangladesh, using a large-scale map. The maps show the composition of the sites in 2010, 2014, and 2017 pre-arrival periods relative to the landscape configuration in 2020, post-arrival of Refugees to the area.

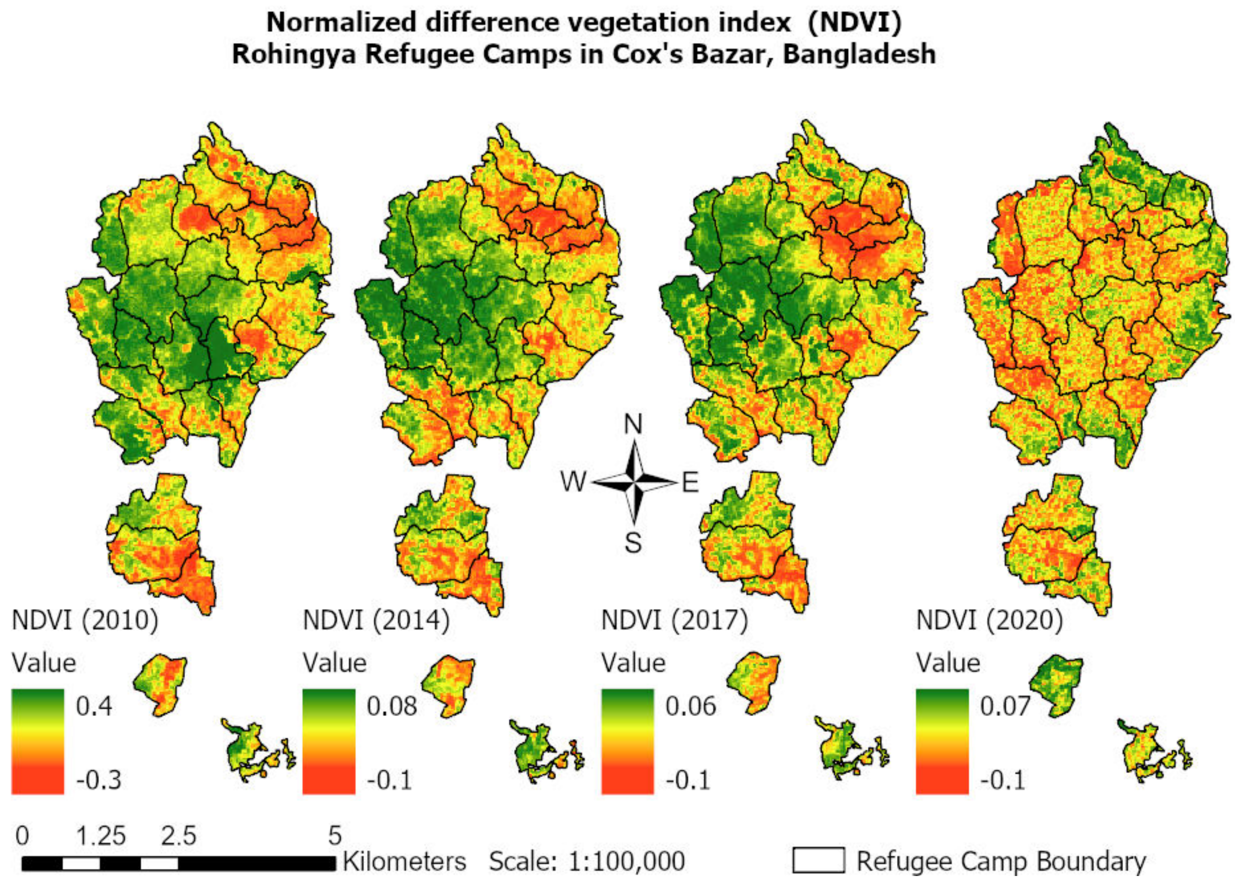


Figure 5: The NDVI Map of the Current Rohingya Refugee Camp Areas. The maps show the campsites' vegetation conditions since 2010.

6.2 Econometric Results

The econometric analysis seeks to evaluate what forest loss we can attribute to the camp openings and observe whether other land cover types are expanding in response to camp openings. By doing so, we can estimate the impact on forest cover relative to a counterfactual estimate with no camps and also collect evidence of what sorts of human activities may be driving these reductions in forest cover.

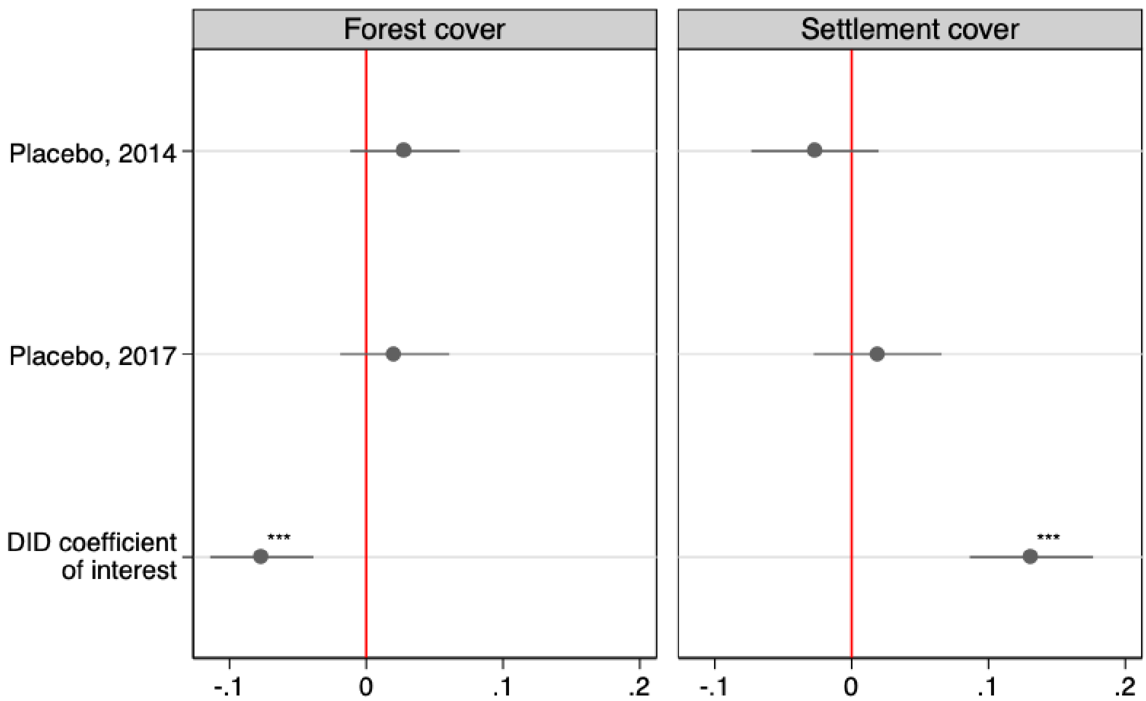
Figure 6 shows the coefficient of interest for the regressions testing parallel trends pre-treatment and the DID coefficient of interest from Equation 1 using binary outcome variables for whether the pixel is forested or is a settlement. Prior to the creation of the camps, we see no significant deviations in the probability of being forested or in a settlement between pixels 0-5 km from the nearest camp (treatment) and pixels 10-15 km away. However, after the opening of the camps, we find that relative to the control area, pixels closer to the camps were more likely to convert from forest cover to another land cover class. After accounting for time-invariant differences across pixels and annual changes that affect the entire region, we find that the probability of a pixel in the 0-5 km buffer around the camps changing from forest to another land cover was 0.076 (7.6 percentage points) higher than for a similar pixel in the 10-15 km buffer area. This estimate is statistically significant at the 0.1 percent level. In 2020, 45.5 percent of the treatment area was forested: the regression estimates suggest that in the absence of the 2017 population influx, 53.1 percent of the treatment area would have remained forested. This loss represents 2,653.7 additional ha of forest lost.[14]

The results from regressions in which the probability of a pixel having settlement cover serves as the outcome variable suggest that when forest cover receded in the treatment buffer, settlements expanded. Again, we find evidence of parallel trends prior to treatment: with placebo treatment years in 2014 and 2017, we see no significant deviation in trends when comparing treatment and control. The main DID estimate is statistically significant at the 0.1 percent level and shows that after camp openings, the probability of a treated pixel being classified as a settlement rose by 0.13 (13 percentage points). This corresponds to an additional 7,681.9 hectares of land converted to settlement.[15]

[14] The treatment buffer contains 349.176 square km of land, which is equivalent to 34,917.6 hectares. In the absence of the population influx, our regression results suggest that $34{,}917.6 * 0.531 = 18{,}541.2$ ha of this area would have been forested in 2020, but due to camp openings, $34{,}917.6 * 0.455 = 15{,}887.5$ ha of this area were forested in 2020. Consequently, we estimate the camp-stimulated losses in forest cover as $34{,}917.6 * 0.076 = 2{,}653.7$ hectares.

[15] Based on pixel estimates, 35 percent of the treatment area was classified as settlements in 2020, which corresponds to $34{,}917.6 * 0.35 = 12{,}221.2$ hectares. The regression results suggest that in the absence of the 2017 population influx, only 22 percent of the treatment area would be settlement, equivalent to $34{,}917.6 * 0.35 = 7{,}681.9$ hectares. These results suggest that due to the population influx of 2017, $12{,}221.2 - 7{,}681.9 = 4{,}539.3$ additional hectares of land converted to settlements in the treatment area.

Figure 6: Coefficient estimates for parallel trends tests and main DID specification



Source: author's calculations using land cover classified maps produced from Landsat remote sensing imagery. Each point represents a coefficient estimate from a separate regression modeled after Equation 1. * $p<0.05$ ** $p<0.01$ *** $p<0.001$. For full econometric results, please see Appendix A3, please contact corresponding author.

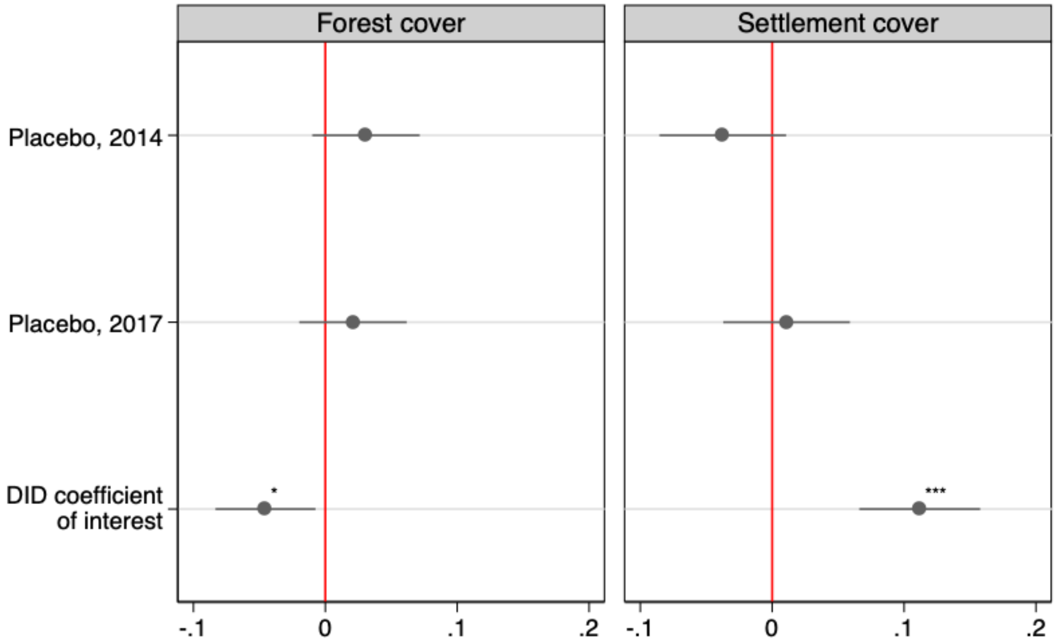
Could the results in Figure 6 be due to the camp populations expanding their settlements beyond camp boundaries in the years prior to fence construction? Our robustness check, in which we omit pixels 0-1 km from the nearest camp borders (Figure 7), suggests that a considerable share of camp-related forest losses took place very close to camp borders. Omitting pixels within 1 km from a camp boundary, the estimated forest loss is smaller in magnitude (4.5 percentage points, relative to 7.6 in the full results) and less significant (5 percent level). Using this result, we can decompose the 2,653.7 hectares of forest loss due to the population influx in the 0-5 km buffer. Approximately 1571.3 ha were lost in the 1-5 km buffer, and the remaining 1082.4 ha were lost in the areas 0-1 km from a camp boundary.

The results for settlement expansion are still statistically significant and quite similar to the main results: we find that after camp opening, the 1-5 km treatment area experienced an increase in the percent of settlement cover by 11.2 percentage points. A Z-test suggests that this estimate is not significantly different from the regression estimate using the 0-5 km buffer as treatment (0.131).[16] We infer that nearly all camp-stimulated settlement expansion is taking place 1-5 km from the camps.

Our robustness check leads us to suspect that two phenomena may be taking place. First, in the 0-1 km buffer, forest areas are declining, and settlement areas are not expanding. If refugees are driving losses in forest cover, it is predominately happening in this area. Between 1 and 5 km from camp boundaries, forests are also receding but are being replaced by settlements. Here, we attribute forest loss to the activities of Bangladeshis moving towards the camps.

[16] Using the following expression to calculate the Z-statistic: $z = \frac{b_2 - b_1}{\sqrt{SE_{b1}^2 + SE_{b2}^2}}$, we use the coefficient estimates and standard errors from our main regression and robustness check and derive $z = \frac{0.111 - 0.131}{\sqrt{.0233645\ ^2 + .0229795^2}} = -0.61$. Given this low z-statistic, we fail to reject the null hypothesis that $b_2 = b_1$.

Figure 7: Robustness check results for parallel trends tests and main DID specification excluding pixels 0-1 km from nearest camp



Source: author's calculations using land cover classified maps produced from Landsat remote sensing imagery. Each point represents a coefficient estimate from a separate regression modeled after Equation 1. * p<0.05 **p<0.01 ***p<0.001. This robustness check drops pixels 0-1 km from the nearest camp border. For full econometric results, please see Appendix A3, please contact corresponding author.

Our analysis of changes in population and nightlights outside camps, reported in Appendix A3 and A4, is largely inconclusive.[17] The control areas exhibited a significantly higher rate of population growth and nightlights than the treatment areas before camp creation, so we reject the parallel trends assumption. It is worth noting that the difference in log population trends becomes smaller after camp opening, which we may interpret as camp areas having an effect, or simply that areas close to the camps started to "catch up" to the population growth in the control area. In the absence of parallel trends, we cannot distinguish between these two hypotheses.

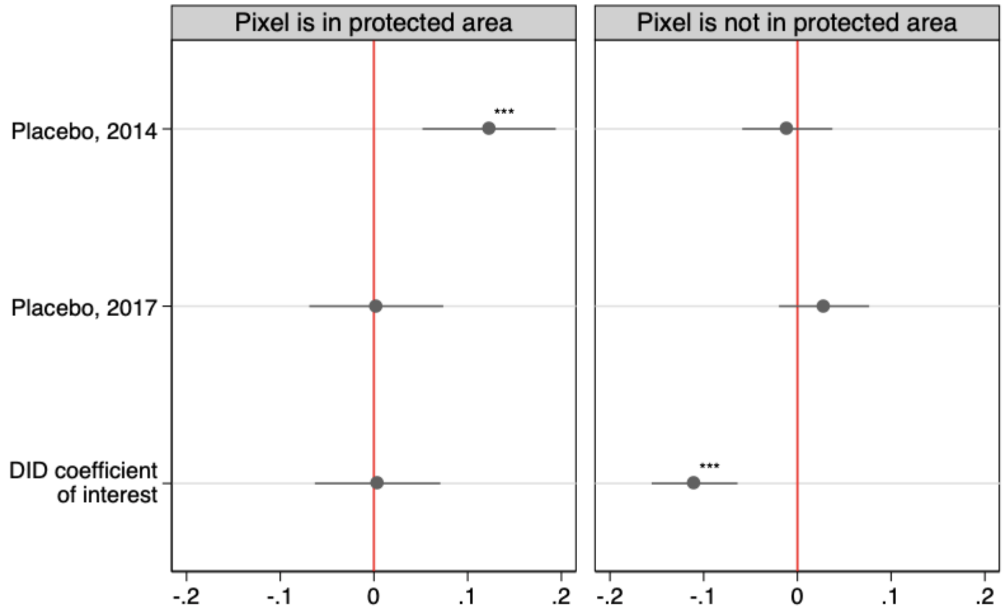
Finally, we find that the significant, camp-stimulated losses in forest cover were concentrated outside protected areas. To estimate the impact for protected areas, we use the same exposure distances to define treatment and control pixels. The treatment pixels all fall within Teknaf Wildlife Sanctuary, which sits adjacent to a large camp area. Control pixels fall within

[17] To obtain the appendix, please contact the corresponding author.

Himchari National Park, which is over 10 km away from the nearest camp. We find no significant change in forest cover in response to the 2017 population influx and subsequent camp openings (Figure 8). This result does not mean that zero forest loss occurred in the Teknaf Sanctuary between 2017 and 2020. Instead, it suggests that rates of forest loss remained similar to those observed in Himchari, despite the fact that only the Teknaf area is exposed to the refugee population. These findings are a positive sign for those concerned about refugee encroachment on the Teknaf Wildlife Sanctuary.

Figure 8 also provides regression outcomes of the estimated impact for non-protected areas by using only treatment and control pixels that do not fall within a wildlife sanctuary or national park. The results suggest that the creation of the camps led to an 11-percentage point reduction in forest cover in non-protected areas. This result is highly significant (0.1 percent level).

Figure 8: Coefficient estimates for heterogeneity analysis: parallel trends tests and main DID specification results estimating on protected vs. non-protected pixels separately, probability of forest as outcome variable



Source: author's calculations using land cover classified maps produced from Landsat remote sensing imagery. Each point represents a coefficient estimate from a separate regression modeled after Equation 1. * p<0.05 **p<0.01 ***p<0.001. This robustness check drops pixels 0-1 km from the nearest camp border. For full econometric results, please see Appendix A3.

7. Discussion

In Cox's Bazar, deforestation has occurred for the past three decades, starting well before the expansion of the refugee camp settlements around late 2017, but the rate of deforestation increased from 2017 with the increase in refugee camp settlements. Between 1989 and 2009, the Teknaf Wildlife Sanctuary (TWS) forest area dropped from 3,304 ha to 1,794 ha, corresponding to a 46 percent reduction (UNDP & UN Women, 2018). Using remote sensing data and a supervised classification algorithm to produce LULC maps of Cox's Bazar over time, including areas within the refugee camps, we find a decline of 16,607 ha in forest cover in Cox's Bazar district. The most significant change in forest degradation occurred between 2017 and 2020. Some of the impacts of deforestation and settlement expansion in the area include habitat and ecosystem degradation, biodiversity loss, human-wildlife conflict, soil erosion, hill cutting, carbon-dioxide emission, and loss of recreational and cultural ecosystem service values (Hassan et al., 2018; Hossen et al., 2019; Mukul et al., 2019; Tallis et al., 2019; Uddin & Khan, 2007).

As part of the overall *impact of hosting* the Rohingya refugees, forest cover losses correspond with refugee camp expansion, as stated in our descriptive spatial analysis. Tree-canopy represents only 2 percent of the official refugee camp areas as of February of 2020, compared to

54 percent before the 2017 influx. An estimated 1,337 ha of forest cover has transitioned to settlements since 2017. However, our estimates of forest cover losses within the camp boundaries is lower than estimates from earlier studies, in which estimates range from 1,619 ha (4,000 acres) to 2,286 ha (5,650 acres) (Hassan et al., 2018; Mukul et al., 2019; Tallis et al., 2019). These differences in estimated forest loss within the camp boundaries could be due to the ongoing reforestation efforts by the UNHCR's Energy and Environment Team working with stakeholders to restore and regenerate green cover in the area.

Our econometric results suggest that the factors driving deforestation in response to camp openings go beyond the direct impact of refugees. We find significant forest losses 0-1 km from camp boundaries that we believe can be attributed to the human activities of camp residents. But in the 1-5 km area from camps, we find considerable evidence that forests are being cleared for settlements. Given extensive limitations on refugee mobility, this settlement expansion most likely represents Bangladeshis moving towards camps in pursuit of camp-related economic opportunities and/or improved access to services. This case study highlights the fact that camps can stimulate forest loss, but for reasons beyond refugee forest product extraction.

In the prior literature, forest loss in Cox's Bazar has been attributed to several mechanisms. These include (a) settlement expansion, (b) development of economic activities, facilities, services, and infrastructural projects, (c) high fuelwood demand leading to loss of forest, and (d) increased population and growing in-migration flow (Bdnews24.com, 2017; Paul, 2017; Tani & Rahman, 2018; UNDP & UN Women, 2018).

First, forest transitions to settlement, including the expansion of refugee camps, is the primary determinant of LULC change, particularly in the district's southern area. Tallis et al. (2019) reported that the camp areas increased by 835 percent between 2016 and 2017, while Hassan et al. (2018) indicated an increase of 774 percent between the same period from 175 to 1,530 ha. For example, the largest refugee campsite, the Kutupalong–Balukhali compound, gained a net settlement growth of 1,219 ha between 2016 and 2017 (from 146 ha to 1,365 ha).

Second, the development of essential facilities, services, and infrastructure projects such as roads, water, sanitation, and hygiene structures are alleged to have contributed to forest cover loss in the region (UNDP & UN Women, 2018). The delivery of these services sometimes comes with direct and indirect impacts on forest cover and landscape alternations. For example, road construction often leads to forest cover loss in many cases.

Third, the high consumer need for essential goods and services accelerated human pressure on the environment and its resources, especially for fuelwood and bamboo extraction. Prominently, the fuelwood demand for domestic household energy use contributed to forest area loss (Bdnews24.com, 2017; Paul, 2017; Tani & Rahman, 2018). According to Uddin and Khan's (2007) study, the average family in the area consumes 6kg of fuelwood per day (Tani & Rahman, 2018). The annual per capita fuelwood consumption in Teknaf was estimated at 1,168 kg (Tani & Rahman, 2018). Before the introduction of the pilot phase of the liquefied petroleum gas (LPG) project in August of 2018, an estimated 6,800 tons (6,800,000 kg) of fuelwood was collected monthly by the Rohingya refugees (UNDP & UN Women, 2018). Scaled up in February 2019 to include more refugee and host population households, the LPG project is anticipated to reduce the local demand for firewood use for cooking. The LPG program, according to UNHCR, has resulted in an "80% reduction of demand for firewood in the Rohingya households in the camps, reducing deforestation to well within sustainable forestry rates, while the overall demand for firewood in the area has dropped to well below pre-influx levels" (UNHCR, 2020c). Additional research is needed to use high-resolution satellite imagery to precisely measure and evaluate the environmental impact of the LPG project in the region.

Besides fuelwood, both Rohingya refugees and the local population rely on bamboo sticks from the forests for shelter construction and other uses. Data from a recent shelter assessment survey shows that 38 percent of all assessed shelters are in "bad condition," 59 percent are in "moderate condition," and only 3 percent are in "good condition." As the primary building material, nearly 99 percent of all refugee shelters currently required both "muli" and "borak" bamboo types for shelter improvement (UNHCR, 2020a). Reports highlight that 63.54±11.99 bamboo culms are needed to construct a refugee family unit shelter (UNDP & UN Women, 2018). According to local reports, the bamboo supply to meet this increasing demand is currently sourced outside Cox's Bazar.

There is anecdotal evidence of the in-migration of both Rohingya refugees (earlier settlers) and the host communities' members (Bangladeshis) towards the camp areas. Current economic activities centered around tourism, including eco-tourism, agriculture (betel leaf farming), aquaculture (shrimp hatcheries), capture fishery, fish processing, accommodation, food services, and wholesale and retail trading, could attract more people to migrate towards the Cox's Bazar district (Filipski et al., 2020). Local reports suggest that assistance provided at refugee camps could potentially influence individuals and households' in-migration decisions.

Though there has been some increase in deforestation due to the expansion of refugee camps in Cox's Bazar, the camps have provided shelter and support for hundreds of thousands of refugees fleeing violence and oppression in Myanmar. Today, nearly 1 million Rohingya refugees have shelters over their heads and appear to be relatively "protected" from escalating violence in Myanmar. The Government of Bangladesh, UNHCR, and several national and international stakeholders recognize that both refugees and their hosts' fundamental human rights, including the right to life, settlement, and protection, should be safeguarded and respected, as enshrined in several international legal instruments.[18]

8. Conclusion

Deforestation has been on the rise for nearly three decades in Cox's Bazar district in Bangladesh. In 2017, over 740,000 Rohingya refugees from Myanmar sought asylum in the district. Humanitarian and socio-economic programs and foreign aid expanded as stakeholders worked to deliver essential services and goods to refugees and (in some cases) host community members. Considering the forest endowment of Cox's Bazar, policy makers and concerned stakeholders inquired about the rate of deforestation as population and development activities increased. Using satellite imagery and remote sensing techniques, this study finds that 12,807 ha of forest cover disappeared across the entire Cox's Bazar region between 2017 and 2020, including 1,337 ha that transitioned from forest to settlement within the 2,545 ha official refugee camp boundary.

Using a simple linear probability model with a difference-in-differences framework to capture changes in land-use / land cover trends in response to camp openings, we find an estimated 2,600 ha loss of forest cover within 1-5 km from the camps triggered by camp openings and local settlement expansions. Additionally, about 7,700 ha changed from non-settlement to settlement. Decomposing this result, we find about 1/3 of forest loss occurs within 1 km of camps, and the remaining 2/3 happens 1-5 km from refugee camps. Are refugees directly driving the results? Our evidence suggests that refugees' direct natural capital extraction *may* be taking place very close to

[18] These include the 1948 Universal Declaration of Human Rights, the 1951 Refugee Convention and its 1967 Protocol, the 2016 New York Declaration for Refugees and Migrants, and more recently restated in the 2018 Global Compact on Refugees.

camps. But 1-5 km away from campsites, forest losses are driven by settlement expansion, most likely for Bangladeshis moving towards the refugee camps.

Policy actions and project interventions could make significant differences in natural resource management, including reducing deforestation rates. Before delivering 1,242,995 liquefied petroleum gas (LPG) to the Rohingya refugee and some host households by UNHCR and partners, refugee dependence on fuelwood for cooking was high. Recently, fuelwood demand has gradually fallen as a direct outcome of the LGP program's rollout. However, refugee reliance on bamboo for shelter construction, renovation, and improvement remain exceptionally high. According to a recent survey, nearly 99 percent of all refugee shelters required both "muli" and "borak" bamboo types for shelter improvement (UNHCR, 2020a). Bamboo extraction is one of several reasons for deforestation and pressures for natural resource exploitation in Cox's Bazar. One of the approaches to lessen deforestation and increase bamboo supply for local uses is to explore the potentials of bamboo farming as a sustainable economic enterprise with livelihood benefits for residents with land ownership or access rights (mostly Bangladeshis). However, access to land and labor market participation constraints faced by the Rohingya refugees could severely limit the positive impact of such activities. Where possible, bamboo farming enterprise could reduce economic vulnerability and prevent environmental degradation in Cox's Bazar. More specifically, a bamboo farm will generate sustainable solutions for meeting the refugees' shelter needs, generating income for Bangladeshis, and significantly contributing to climate change mitigation through the incredible carbon sequestration and storage capacities of treated bamboo materials used in building construction (Correal, 2019; Huang, Ji, & Yu, 2019; Silva, Farbiarz, & Silvasy, 2019; Trujillo & López, 2019; Yuen, Fung, & Ziegler, 2017). To assess the complexities of this sustainable enterprise, we recommend a follow-up cost-benefit analysis study to evaluate the net benefit of bamboo for sustainable shelter and climate change mitigation in Cox's Bazar. For example, the land-cover type to be substituted with bamboos could be studied in detail using high resolution remotely sensed data.

Another critical policy question is whether there would be significant forest cover loss if refugee hosting in Bangladesh took a more integrated approach. Past studies suggest that integrated refugee populations are less likely to rely heavily on natural resources, more likely to find alternative sources of income and livelihood strategies, more likely to get assistance from members of their host communities, and very likely to comply with local rules and regulations due to social pressure (Cassels, Curran, & Kramer, 2005; Codjoe & Bilsborrow, 2012). Similarly, co-management of natural resources between the local communities and their governments, reinforced with increased enforcement of environmental regulations, could further deter the overexploitation of natural capital assets and flows (Dampha, 2020; Ostrom & Cox, 2010). Hence, including both local Bangladeshis and Rohingya refugees in the sustainable management of land and forest resources may yield positive environmental outcomes. This is because both Bangladeshis and refugees are heavily natural resource dependent. Focusing on both groups could promote more economic integration through local business interactions as evident in a recent study (Filipski et al., 2020a). Besides, refugee inclusion can facilitate a “systematic natural integration” and enhance shared responsibility over natural resource management. More efforts to understand how natural or policy driven integration influences natural capital extraction and land cover change are needed in this context. Future studies will also enrich our understanding of camps and forest losses by learning more about those residing in the new settlements near the refugee camps in Cox’s Bazar. What subset of the Bangladeshi population do these migrants represent, and what induced these populations to move close to the refugee camps? Such a study can also highlight the benefits for those hosts who chose to live very close to camps.

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