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Creating a GIS-Based Environmental Vulnerability Index for Rohingya Refugee Populations in Bangladesh

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No portion of the work references in this thesis has been submitted in support of an application for another degree or qualification of this or any other university of institutes of learning.

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ABSTRACT OF THESIS submitted by:

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The Rohingya refugee crisis in Bangladesh started since August 2017, following a sudden influx of refugees fleeing ethnic violence from the Rakhine region of neighboring Myanmar. More than a million refugees have settled in the Teknaf region of Bangladesh, in Kutupalong Refugee Camp, an overcrowded makeshift settlement that has since become of the world's largest refugee camps. The camp is situated in an area that used to be previously forested, leading to deforestation, which has made the camp's inhabitants vulnerable to environmental hazards. Some of the problems facing them include lack of healthcare, nutrition, sanitation, and risk of landslides and flooding during the monsoon. This study quantified the rate of deforestation using remotely-sensed imagery, and found that since the start of the crisis, Non-Forest area has seen a gain of 34 square kilometers, and Forest area has lost 15 square kilometers Out of 79 square kilometers of the study area, a total of 47 square kilometers are denuded in 2019. The study also used secondary data to develop an environmental vulnerability index based on Principal Components Analysis to find that camps 3, 4, 26, 15 and 13 are the most vulnerable areas of the camp. It is hoped that knowledge of using limited data from the field combined wish GIS based technologies to create an index for measuring vulnerability can be applied to ensure more efficient planning and service delivery for faster and improved humanitarian response. Based on the results of the vulnerability analysis, recommendations were made for public and private actors operating in the Kutupalong refugee camp.

Keywords: Remote Sensing, Land Change Analysis, Bangladesh, Rohingya, Migration, GIS, Vulnerability, Vulnerability Index, Principal Components Analysis, Deforestation, Mapping

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List of Abbreviations

EVI – Environmental Vulnerability Index

GIS – Geographical Information Science

NDVI – Naturalized Difference Vegetation Index

PCA – Principal Components Analysis

ROI – Region of Interest

SCP – Semiautomatic Classification Plugin

1. Introduction

1.1. Background

The Rohingya Refugee crisis, a recent escalation of a historic phenomenon, is one of the fastest growing refugee crises the world had ever seen. The Rohingya ethnic population, living in the Rakhine state of Myanmar, have been victims of targeted violence since the 1970's due to historical tensions. Bangladesh, neighboring Myanmar, has had waves of refugees in the 70's, 80's and 90's, who have settled in the Southern district of Chittagong (Rahman 2015). Since October 2017, Bangladesh has faced the largest onslaught of refugees fleeing ethnic violence perpetrated by the military and militias in neighboring Myanmar. They have been temporarily settled in the coastal region of Teknaf in Bangladesh, in a sprawling and over-populated refugee camp called Kutupalong refugee camp (Vince 2019). The current population of the camp exceeds 1.8 million, and there are now illegal settlements outside of the main camp, contributing to the continued expansion of the camp periphery. The total area of the camp is roughly 30 square kilometers, which makes it an incredibly densely settled area.

High population density of the camps has led to environmental hazards and degradation in the neighboring area. The location of the camp itself is in an area that was previously forested with old growth species. The camp's existence has led to wide-scale deforestation and forest cover loss, quantified at a growth rate of 774% percent from 2016 to 2017 based on satellite imagery (Hasan et al. 2018). Deforestation, combined with the pressures of a growing population, has led to compound environmental effects that the refugee population is exposed to, such as risk of landslides, flooding, and human-animal conflict.

There have been a few studies to analyze the impact of the refugee camp on the surrounding environment. Satellite data is especially useful for this type of analysis due to a lack of secondary data, often in the immediate aftermath of a disaster. Many of these studies have utilized geospatial data and Geographical Information Science (GIS) for the analysis. Some studies have used GIS-based approaches to creating vulnerability indexes based on factors such as gender or wealth to identify patterns of unequal exposure to risks within the camps. However, a holistic environmental vulnerability index to gauge which areas of the camp are at the greatest risk of environmental hazards has not yet been developed.

1.2. Research aims and objectives

This thesis aims to develop an environmental vulnerability index of the Rohingya refugee camp (including the Kutupalong refugee camp, or the main camp, the peripheral unofficial camps including extension sites and the Southern part) based on a number of factors. Population of the camps, number of families with vulnerable populations, concentration of basic services (health and sanitation), risk of landslide, and risk of flooding are the variables considered for this study. The study seeks to answer a set of questions in two steps –

i) What is the extent of forest cover loss in the refugee camps and surrounding areas?

ii) Are certain areas of the refugee camps more vulnerable than others?

In order to answer these questions, I will -

- Collect the necessary data based on satellite imagery and secondary data sources
- Analyze the extent of deforestation in the camp area based on satellite imagery

- Establish a suitable method for creating an environmental vulnerability index and
- Create an environmental vulnerability index for the camp

The overarching aim of this thesis is to deliver an environmental vulnerability index to measure the differential vulnerability risk of communities in order to deliver humanitarian aid more effectively. This will be achieved based on limited data availability in the field, and will be supplemented by geospatial data.

1.3. Thesis outline

Chapter 1 of the thesis provides the background and justification for this thesis, including the historical context behind the Rohingya Refugee Crisis, the extent of the current environmental degradation in the area, based on various reports and the usefulness of GIS-based approaches to vulnerability index creation. **Chapter 2** consists of a literature review, including the different frameworks for environmental vulnerability that are commonly used. It also contains my adaptation of the commonly used frameworks, and explanations for the adaptations, including the definition of vulnerability in the context of the Rohingya. The different types of environmental vulnerability indices that are used for index creation are also surveyed in this chapter, along with examples. In **Chapter 3**, the research methodology is described in details. The sub-chapters include the data collection methods employed for gathering remotely-sensed data and other statistical data, descriptions of the remote-sensing processes used to quantify forest cover loss, description of the Principal Components Analysis performed to calculate the index and the justification behind each of these methods. **Chapter 4** contains the main body of the research, including a systematic description of the analysis. It shows the remote sensing and statistical analysis process, including the process of the index creation, and includes the maps that were generated along the way. **Chapter 5**

contains the discussion of the results, significant findings, and implications of the research for camp management, relocation and future studies in times of crisis. It also includes all maps developed during the research, and a discussion of the limitations of the study. **Chapter 6** is the concluding chapter, and summarizes the research and key findings. It also contains recommendations for future research.

2. Literature Review

This chapter focuses on the conceptual frameworks for vulnerability that have defined and directed the study. The concept of “environmental vulnerability” is described and the linkage between vulnerability and environmental vulnerability in particular is explored through examples of how different indices are created to determine environmental vulnerability.

2.1. Frameworks for vulnerability

There are more than 20 different formulations for what vulnerability can be defined as. It is more of a concept rather than a clear definition. Yet, it is necessary in environmental research to identify social, environmental and economic factors that influence people. According to the Hyogo Framework for Action, indicators for vulnerability ought to be developed for environmental analysis, even in spite of the variability regarding the exact definition of vulnerability (Birkmann 2006). The term ‘vulnerability’ is thus defined in numerous ways by many different communities of researchers and scientists. In general, the commonly held understanding of vulnerability can be articulated by this definition - ‘’Vulnerability is the degree to which a system, subsystem, or system component is likely to experience harm due to exposure to a hazard, either a perturbation or stressor.’’ (Turner *et al.* 2003).

This basic definition of vulnerability can then be expanded to meet the breadth and scope of any particular scenario or study area, such as the vulnerability of refugees to various socio-economic factors. The concept has been expanded upon by the United Nations Refugee Agency (UNHCR) in its efforts to improve aid effectiveness during the Syrian refugee crisis. According to the UNHCR on vulnerability among Syrian refugees, the conceptual framework or vulnerability includes stressors primarily in relation to protection threats, inability to meet basic needs, limited access to basic services, and food insecurity, along with the ability of the population to cope with the consequences of this harm (alnap.org). A lack of research on what vulnerability means for refugee populations has led the UNHCR to characterize vulnerability as a factor that is differential in how it affects various groups of people, scale dependent, and changing in intensity or characteristics over time.

According to Turner *et al.*, vulnerability in environmental and sustainability sciences dwells on the sensitivity of a population to environmental stressors or hazards. Environmental vulnerability, or the study of risk reduction when faced with disasters, considers vulnerability to be the result of biophysical and socio-economic factors. This formulation is linked to the nature of hazards themselves, which can be biophysical, such as floods, landslides and hurricanes, or socioeconomic, such as poverty. This linkage can be summarized as a process or factor that increases a community's likelihood of damage as a result of an anthropogenic or natural event contributes to that community's vulnerability (Birkmann 2006).

The IPCC adapts this conceptual framework of vulnerability to form a definition for climate vulnerability, which it defines in the IPCC Third Assessment Report (TAR) as "The degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity." (IPCC 2001, p. 995) Environmental vulnerability is often a subset of social vulnerability, as the various biophysical factors that can increase vulnerability are often caused by socially created factors, such as deforestation.

This underlines a key dimension in the conceptual framework of vulnerability, which is the adaptive resilience, or coping capacity of the community that is at risk. Turner's definition of vulnerability is particularly applicable to the case of refugees as it provides room for the inclusion of factors which make refugees as a group be particularly vulnerable to environmental hazards. According to him, vulnerability can be explained through the idea of "entitlements, coping capacity, and resilience." The concept of entitlements demonstrates why certain groups are differentially at risk of hazards, which could be any number of socio-economic factors. In the case of the Rohingya, the primary entitlement to vulnerability is ethnicity and poverty, as they are both the victims of ethnic violence and are suffering from poverty. Coping capacity refers to the ability of the said group of people to cope with the stressors they face, based on the "endowments" that they have. The group's endowment is its capacity to access various social safety-net structures.

In the case of the Rohingya, their endowments would include access to social welfare benefits such as healthcare or sanitation. A group with more endowments will be less vulnerable to the impacts of disasters. It is important to include social, economic and political structures in the conceptual framework of vulnerability analysis, as it is these power structures within society that dictate the condition of marginalized groups. The third concept, resilience, refers to the amount of hazard that a given community or population can counter without disintegrating into a different, inferior state. The faster a community can rebound to its previous state, the more resilient it is. Adaptive capacity is an offshoot of the idea of resilience, and refers to the ability of a community to become more efficient in rebounding to its original state due to its experience of a hazard.

2.2. Commonly used environmental vulnerability indices

Vulnerability analysis is considered to be effective if it addresses certain criteria, such as the inter-connectedness of systems that lead to the compound effect of hazards. An effective analysis must be geographically applicable to a smaller region, while staying within the context of broader principles. It must make use of all available quantitative and qualitative data in novel ways to reveal linkages which may be contributing to vulnerability, while contributing to the development of metrics for measuring vulnerability or adapting to hazards. (Turner *et al.* 2003).

However, the analysis of environmental vulnerability is different from a vulnerability analysis purely focused on social vulnerability, as the measurement of environmental indicators are often not expressible in uniform and standardized units. Environmental factors are coupled with socio-economic factors, leading to fuzziness in environmental vulnerability analysis (Kaly *et al.* 1999). Therefore, the creation of environmental indexes requires the inclusion of both natural and anthropogenic factors.

. Previous environmental vulnerability indices have focused on the impact of environmental hazards on humans and human systems. The main environmental vulnerability index in use today is the EVI (Environmental Vulnerability Index) developed by the South Pacific Applied Geoscience Commission (SOPAC) to measure risks facing the environment. However, the term environmental vulnerability index can be applied to indices in which the main responder is humans, and the factors acting upon them are environmental. Most environmental indices focus on as small number of factors acting upon a localized area, while the EVI is applicable for comparisons on a country-level.

The EVI incorporates three different kinds of data. It incorporates historical risk exposure data to measure potential risk using the REI (Risk Exposure Sub Index), it uses factors contributing to coping capacity in IRI (Intrinsic Resilience Sub Index) and it includes anthropogenic and natural forces acting upon a country using the EDI (Environmental Degradation Sub Index). These sub-indexes are amalgamated to form the EVI.

However, for this study I find that the EVI's methodology is not applicable, due to the differences in scale and the difference in primary responder to hazards. In this context, vulnerability indices localized for small-scale studies are more appropriate. A review that looks at over fifty different studies which incorporate environmental vulnerability indices finds that the indices amalgamate biophysical and socioeconomic issues to form indices using many different methods (Nguyen *et al.* 2016). Most of them focus on an internal and an external set of factors, wherein internal refers to a system's own coping capacity and external refers to biophysical and socioeconomic hazards a system is exposed to. Generally, most climate vulnerability analysis contains a segment based on GIS to show the spatial distribution of vulnerability.

Both conceptualizations of vulnerability and the methodological approaches for index creation vary from discipline to discipline and based on context. There is no standard for creating a vulnerability index. Commonly, the vulnerability indices studied select indicators for vulnerability based on context, and incorporate a predictive model. According to Nguyen et al, most environmental and climate vulnerability indicators are chosen based on a data-driven, theory-driven or expert-driven approach. The index methodology for this research study is a combination of theory-driven and expert-driven approach, informed by the theoretical framework outlined above and the analysis of vulnerability literature in the context of the Rohingya discussed below.

2.3. Vulnerability in the context of the Rohingya

Based on these understandings and definitions of vulnerability, in this study, the meaning of the word "vulnerability" for Rohingya populations is the degree to which they are differentially exposed to environmental hazards based on their status as refugees. The main stressors that affect them are the same as those consistent with a lack of socio-economic endowments and an unequal exposure to biophysical hazards such as landslides and floods. The endowments available to the refugees are reflected in their access to sanitation and healthcare, and their coping capacity is a function of these endowments. It is harder to characterize resilience within the scope of this study due to limitations in data availability. It is hoped that the mappings of the distributions of these resources and the evolving deforestation patterns reveals the spatial and temporal dimensions of these hazards. An investigative EIA conducted for the Swedish Civil Contingencies Agency identified factors which were being negatively affected or were negatively affecting the refugee populations, which required steps for mitigation (de Vries *et al.* 2017). These included hazardous and non-hazardous waste, climate change risk, fragile ecosystems, deforestation and energy demand, waste and health, among other factors.

An article in the Lancet by a group of doctors in the Rohingya camps succinctly puts into words the challenges, threats and hazards facing the Rohingya (Ahmed *et al.* 2018). According to the report, the biggest socio-economic threats facing the Rohingya are – mass overcrowding occurring in the camps, which housed nearly a million people at the time the article was written; a lack of healthcare resulting in disease outbreaks such as diphtheria; food shortages; poor access to sanitation and water. They also suffer from malnutrition related health diseases such as anemia (Leidman *et al.* 2019). Among the biggest biophysical threats are factors such as landslides, flash flooding and cyclones affecting the area in the monsoons. The population there is at an increased risk of morbidity due to the drastic impact a disaster would have on them. While there have been historical efforts to deliver reproductive healthcare and treatment of water-borne diseases among the Rohingya population, there has been a lack of focus on mental health provisions, which may be affecting their overall adaptive capacity (Sultana 2011). Over time, the lack of resources such as cooking gas and such means that the community has to forage in the surrounding areas for firewood. This has contributed to the deforestation that has already occurred in the once forested

According to the latest report by the UN Office for the Coordination of Humanitarian Affairs (OCHA), 1 to 7 July 2019 witnessed 136 natural disaster related incidents affecting 18,000 in the Rohingya refugee camps (OCHA 2019). This brings the total number of people affected from flooding and landslides since the start of the 2019 monsoon season in April to nearly 38,500, with 8 official mortality reports. This shows that the nature of vulnerability within the refugee camps can mainly be grouped into population-related risks, weather-related risks, and service-availability related risks. Though long-term food sources are not stable or secure in the Rohingya camps due to the complete reliance on humanitarian aid as a means of feeding the population, all of the approximately 1 million camp residents have adequate access to food. According to the latest figures from the World Food Programme, 80 per cent of total refugees only have WFP food assistance as their source of food (WFP 2019). WFP spend 24 million dollars per month to feed 900,000 refugees in the camps, with the other refugees receiving food assistance from various NGO's.

2.4. The use of Remote Sensing in quantifying deforestation

Remote sensing can be defined as "the measurement of reflected, emitted or back-scattered electro-magnetic radiation from Earth's surface using instruments stationed at a distance from the site of interest." (Roughgarden *et al.* 1991). This allows remote sensing satellites to capture non-visible bands of information, such as Near Infra-Red or Short Wave Infra-Red. Remotely sensed imagery is often used to quantify rates of deforestation around the world.

The use of this methodological approach to classifying land cover has gained popularity with the development of higher quality satellites with sensors that can detect multiple types of information. It is a popular method for analysis in tropical areas or disaster-prone areas that are hard to access (Weishampel *et al*. 1996). One of the main benefits of remotely sensed data is in the fact that it can be combined with biophysical and socio-economic data (Chowdhury 2006). Spatial analysis helps to identify the trends and patterns of land use and land cover change in an area, while also identifying the drivers behind this change. It allows for taking snapshots from different time periods, which can then be compared to a reference time period to analyze how land cover has changed.

The other primary use of remote sensing is to identify vegetation health. It can be used to identify the extent of tree cover, areas of vegetation loss, and other spatial properties of the canopy, such as density. The widespread availability of data for each month, from every inch of the globe makes it possible to use remote sensing as a tool for understanding and predicting land use patterns and assessing rates or extent of deforestation across both global and local extents. Indexes such as Naturalized Difference Vegetation Index (NDVI) are primarily used for assessing vegetation health (Kumar 2011).

There are currently a number of satellites that enable the observation of land cover at varying spatial and temporal resolutions. The best known satellites include NASA's Landsat (at 30 meter resolution), Sentinel (at 10m resolution) and Terra (250 meters). The spectral signatures of land cover classes are detected through analysis of pixel values, and then used for the classification of land cover.

3. Research Methodology

This chapter details the data collection process and sources of data acquisition. It describes the process behind acquiring remotely-sensed imagery, as well as secondary data collected from websites of various agencies. It contains descriptions of the mathematical model used for the index creation, and describes the land cover change analysis that was conducted, as well as descriptions of the various geospatial analysis processes that are conducted for the study such as land cover classification.

3.1. Selection of the case study area

The case study was selected based on the camp designation by the UNHCR. The UNHCR officially designates 23 camps, with Kutupalong RC being the oldest. This thesis standardized all secondary data collected based on the unique camp IDs. The satellite data was cropped using QGIS to provide a window of the camp and surrounding areas based on the GPS coordinates for the camps. There are existing datasets that contain the existing boundaries of the maps that adhere to the UNHCR's designation. The camp area was determined based on these existing boundaries and visualized according to the needs of this study.

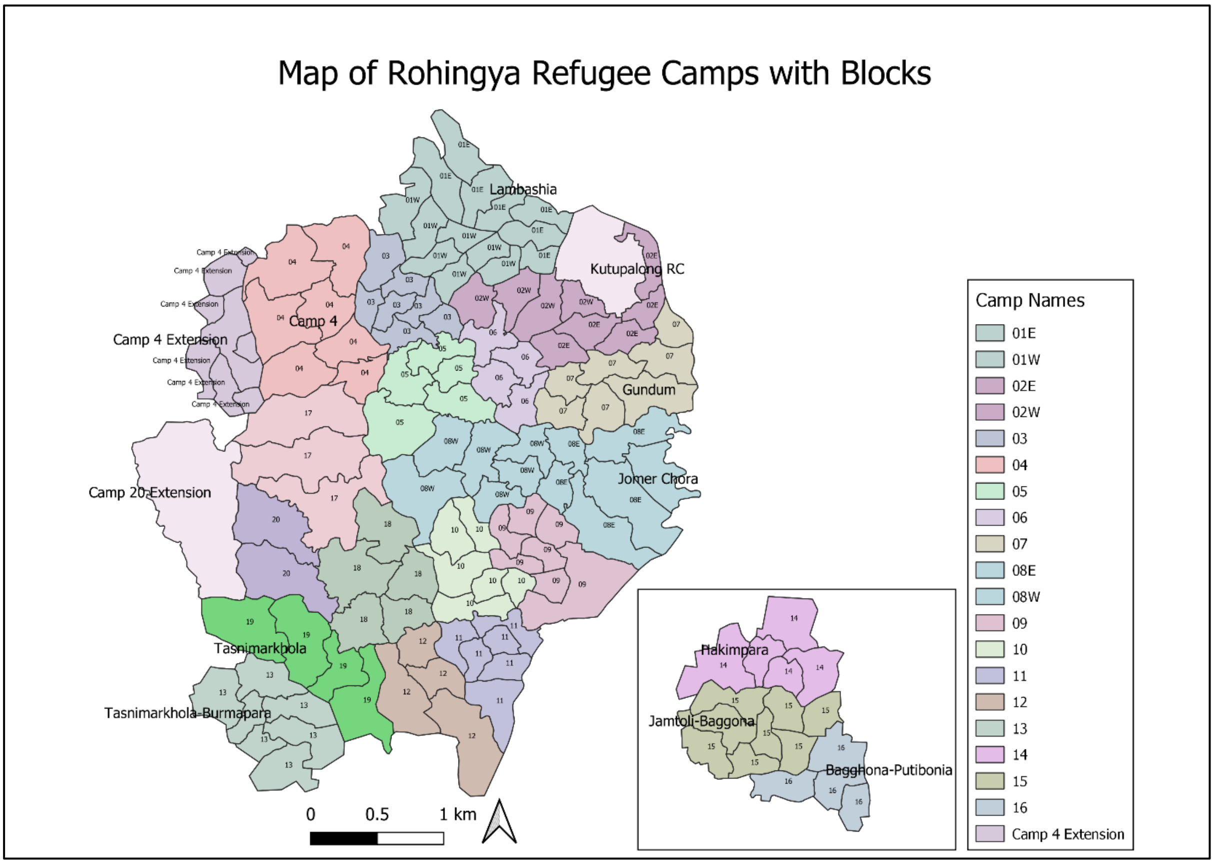


Figure 1 Map showing the different camp blocks within the Rohingya refugee camp. The inset shows the Southern tip of the camp. Dataset: Inter Sector Coordination Group (ISCG)

3.2. Data collection

The main data was collected from Humanitariandata.org, a website which contains data about ongoing humanitarian crises around the world. The population topline figures were taken from UNHCR's "Refugee Response in Bangladesh" portal. Sanitation data that was used to create the index was collected by the NGO called REACH between September and October of 2018. Data on healthcare and risk of floods and landslides was based on UNHCR data from 2018. Data for the camp boundaries and blocks were downloaded from Humdata.org from the directory of the Inter Sector Coordination Group (ISCG). Appendices VIII and IX contain examples of how the data was standardized.

3.2.1. Remotely sensed data

Remotely sensed data was downloaded from the open source website EarthExplorer (earthexplorer.usgs.gov) of the United States Geological Survey (USGS). It is an archive of satellite images, aerial photographs, and cartographic products made available through USGS. For the land change analysis, high-resolution (10m) data from three time periods was downloaded from the Sentinel 2A and 2B satellites operated by the European Space Agency. The three time periods selected were:

- 2016-11-30, which served as the pre-refugee influx backdrop for the analysis
- 2017-11-30, which showed land change and forest loss patterns in the year of the refugee influx and settlement, and
- 2019-04-24, which provides a snapshot of the current state of the forest surrounding the camp's expansion

3.3. Types of analysis

The index was created using the data collected from different sources. As such, they all contained different camp names and variables. The data was sorted and cleaned manually to derive number of individuals or population, number of latrines, number of healthcare facilities, number of families with special needs, percentage of flood risk, and percentage of landslide risk associated with each camp.

3.3.1. Principal Components Analysis

The main methodology used for creating the index was principal components analysis or PCA. PCA is used to reduce or compress a large number of factors by creating two new axes based on the directions of maximum observations among the variables. This was the preferred method of index creation due to the benefits associated with PCA – it combines both continuous and discrete variables, and results in the least number of distortions (Abson *et al.* 2012). The new axes produced are the principal components. Though the importance of the factors selected were determined based on qualitative research on the factors affecting Rohingya refugee populations, it was difficult to decide on the appropriate weighting method or aggregation method for the index creation. Another method that was considered was a heuristic methodology (Rivera *et al.* 2014) for weighting based on literature review and mentions of multiple variables, though it was not implemented due to a lack of sufficient data and shortage of time. Principal components analysis was useful in this case due to its ability to reduce a large number of variables into a few principal components. This method was chosen because it allows for using a large number of data, whether they are continuous or discrete. It is appropriate for this research, which aims to identify regions that are more vulnerable. This method of finding trends in the data can be ineffective if the data is distributed in any other way than multivariate normal distribution, as it large relies on finding orthogonal principal components. PCA's limitation arises if the data contained is not linear. It is not an appropriate method for scale-dependent data (Kai-Hong 2007). It is an appropriate method in this case as it removes the influence of noisy variables. Appendices V, VI and VII contain the tables generated during the analysis.

3.3.2. Land Change Analysis

The remotely-sensed data was processed in multiple stages using QGIS, an open source GIS software. All bands of the data were downloaded from the Sentinel 2A and B satellites, and were converted to their surface reflectance values. Following this, the data was clipped to the extent of the camps and surrounding areas in order to facilitate processing time. Three bands – band 8 (Near infra-red or NIR), band 4 (Red) and band 3 (Green) were used to create false color composites for the three time periods (Figures 2, 3, and 4). In these false color composite images, healthy vegetation is identified by the bright red, poorer quality vegetation is indicated by the dark red, water is indicated by the dark blue, and non-forested land or camp area is indicated by the bright blue or white. False color composites are created to identify the different classes of pixels more easily.

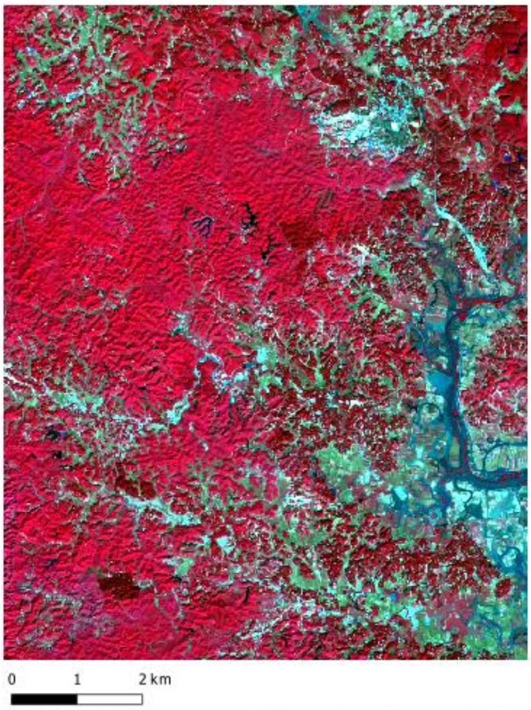


Figure 2 False color composite of the Kutupalong camp area prior to the Rohingya influx. In it, the vast expanse of red reveals that the region was heavily forested prior to the settlement.

Figure 3 Satellite image from November 2017 showing the camp's formation three months into the crisis.

Figure 4 Image captured in 2019 showing the expansion of the camp area. The deforested area can be seen to have expanded and the camp has expanded westwards.

As the next part of the remote sensing process, spectral signatures of the different types of land cover were derived from the bands using training sites. The land cover was classified into several micro classes, and training sites were created for each micro class. The classes were combined using reclassification to form the macro classes. Spectral distances were calculated to ensure that the training sites were effectively identifying each macro class without overlaps between classes. A maximum likelihood classification was then performed to classify the land cover into three categories – forest, non-forest and water. A 2017 study that aimed to quantify the camp area of Kutupalong refugee camp found that next to digitization as a method of classification, a supervised calculation was the most effective in successfully quantifying land change (Biella 2019). As I also aimed to develop an NDVI index, the digitization method was not the most appropriate one for this study.

Three classes were used because the aim of the land cover change analysis is to understand the extent of deforestation as a result of camp expansion. Moreover, the area did not contain farmlands prior to the settlement of the refugees, and was densely forested. Therefore, all of the bare soil visible was the result of deforestation. It was important to make a separate class for water, as the water level rises and drops depending on the dry or wet season. It is important to identify whether the increase or decrease in forest cover or is due to a change in the water level, which should not be considered as deforestation. An average of 30 ROIs were used for each land cover class. A maximum likelihood classification was carried out using the SCP plugin in QGIS. Spectral signature plots were calculated to separate the spectral signatures of the different classes, and to avoid overlaps. The forest and settlement classes were often overlapping, and to differentiate between the two the spectral signature plots had to be extended.

A maximum likelihood classification method was used to classify the pixels. The probability of each pixel belonging to a particular class was calculated using an algorithm, and the pixels were defined based on probability and also the spectral signature. The classification was conducted based on macro classes rather than classes, as this allowed for accurate classification of each area of similar pixels, such as vegetation at a slope or inundated bare soil. Following this, SCP was used to derive information on pixel change in each class to arrive at the final figures. Refer to appendices II, III and IV for detailed information on the pixel transitions.

3.3.3. Normalized Difference Vegetation Index (NDVI)

A Normalized Difference Vegetation Index (NDVI) is a common geospatial tool used to measure the health of live vegetation. Live vegetation absorbs solar radiation during the photosynthetic process, and then re-emits in the in the near infrared wavelength. The rationale behind using this method for gauging the health of vegetation is due to the fact that bare soil tends to reflect the red wavelength (Pettorelli *et al.* 2005). Therefore, a ratio of the differences in the visible and invisible red wavelengths makes it possible to use this as an accurate and effective way to measure the quality of vegetation in an area. The more densely vegetated the area is, the more NIR is reflected, and so the NDVI is able to provide information not only on whether an area contains vegetation, but also on how dense the vegetation is. As a result of the NIR and Red reflectance being within the range of 0.0 and 1.0, the NDVI is categorized into a range from -1.0 to +1.0. This makes it simple and appropriate for lay people to understand. The NDVI was created using the satellite data of the three time periods.

3.3.4. Data validation and field visits

I visited parts of the camp to gain an overall understanding of the living conditions of the camp's inhabitants and the most important factors determining the camp's vulnerability to environmental hazards. The other purpose of the field visit was to check the accuracy of the land cover classification for 2019. This was done by establishing ground truth points based on GPS coordinates. I visited these sites and subsequently plotted the GPS coordinates from these into the classification maps. 9 points were chosen, with 3 points for each category. Refer to Appendix I for more information on the ground points.

4. Data Analysis

This chapter contains a detailed analysis of the various data analysis methods that were employed in this study. It contains descriptions of the Principal Components Analysis process, as well as the mathematical model used for the index creation. It also contains the maps produced during the land cover change analysis that was conducted.

4.1. Field observations

A ground visit to Kutupalong Rohingya camp and surrounding areas revealed the true extent of the humanitarian and environmental crisis that has unfolded over the last three years in the Chittagong Hill Tracts of Bangladesh. The widespread human misery is apparent in the sea of blue tarpaulin covered huts spreading for as far as eyes can see. As the field visit occurred in the monsoon season, the area was covered in muds and partially flooded, blocking access to certain parts. The huts where more than a million people lived as stateless refugees were not adequate shelter against the monsoon rains, thereby pointing out the most obvious biophysical source of vulnerability among the population – rainfall. Most people in the camps were malnourished and bare feet. The waterlogged surroundings were prime breeding grounds for zoonotic diseases such as cholera, typhoid, or diarrhea, and diseases carried by vectors such as Dengue fever or malaria. While some latrines were present, they were in unsanitary conditions, and there were no special provisions for women or disabled people.

The widespread present of foreign and local aid agencies and NGOs was highly visible. Large camps were run by organizations such UNHCR, Save the Children, Medecins Sans Frontieres, Red Cross and WFP. They provided food, education and primary healthcare to the camp's residents, thereby contributing to the development of their adaptive capacity. Of particular interest were the many innovative adaptive solutions that are employed by the Rohingya to cope with the daily threats they face. Many of the huts were fitted with solar panels – some brought by the refugees when fleeing ethnic violence, and some distributed by aid organizations. Most of the technology used by the Rohingyas were based on solar energy, such as solar rechargeable transistor radios or solar powered phone chargers. Gas cylinders were increasingly being used in place of firewood. There was evidence of adaptive architecture, as many houses were fenced with bamboo plants to prevent soil erosion during the rains.

As there were no legal options for the Rohingya to earn an income, many of them had established a barter economy by selling materials received as aid, such as extra clothes, sanitary products and tools. Overall, the Rohingya refugee crisis and settlement has caused contradictory effects on the socioeconomics of the area. They are working as cheap labor illegally and selling aid materials at lower price points than the market. At the same time, the influx of foreign aid workers has exponentially increased the prices of goods and services in the area. Hotel rooms, accommodation, transport and food are also grossly overvalued. However, there are many new jobs in the market, as locals are becoming involved in providing services for the aid workers. I noticed the development of many new buildings, restaurants and cafes catering to a foreign clientele.

The environmental costs of the unplanned development and expansion of the camp site are also evident in the barren land with red soil, which indicates that the land was once fertile. The camp site is surrounded by trees in the border, which used to be thick tropical forests in the past. Parts of roads were caved in due to landslides. Enormous amounts of waste were being generated, most of it being composed of single use plastic and lithium ion batteries. There is currently no large scale recycling or safe disposal initiative in place for dealing with the waste. The field visits revealed that all 9 of the ground truth points were categorized correctly in the land cover classification for 2019.

Figure 5 Picture of the study area taken during field visit

4.2. Data visualization

To gain an understanding of how the variables selected affected the outcome of the final index and to understand underlying spatial patterns, the data collected was visualized. Below, a map of population distribution in the Rohingya camps is included. This gives an idea of which areas may be more vulnerable due to overcrowding. It appears that the areas which were settled in earlier are the more populated ones. This hinted at the possibility of using these variables to do the principal components analysis, as they are variable from camp to camp.

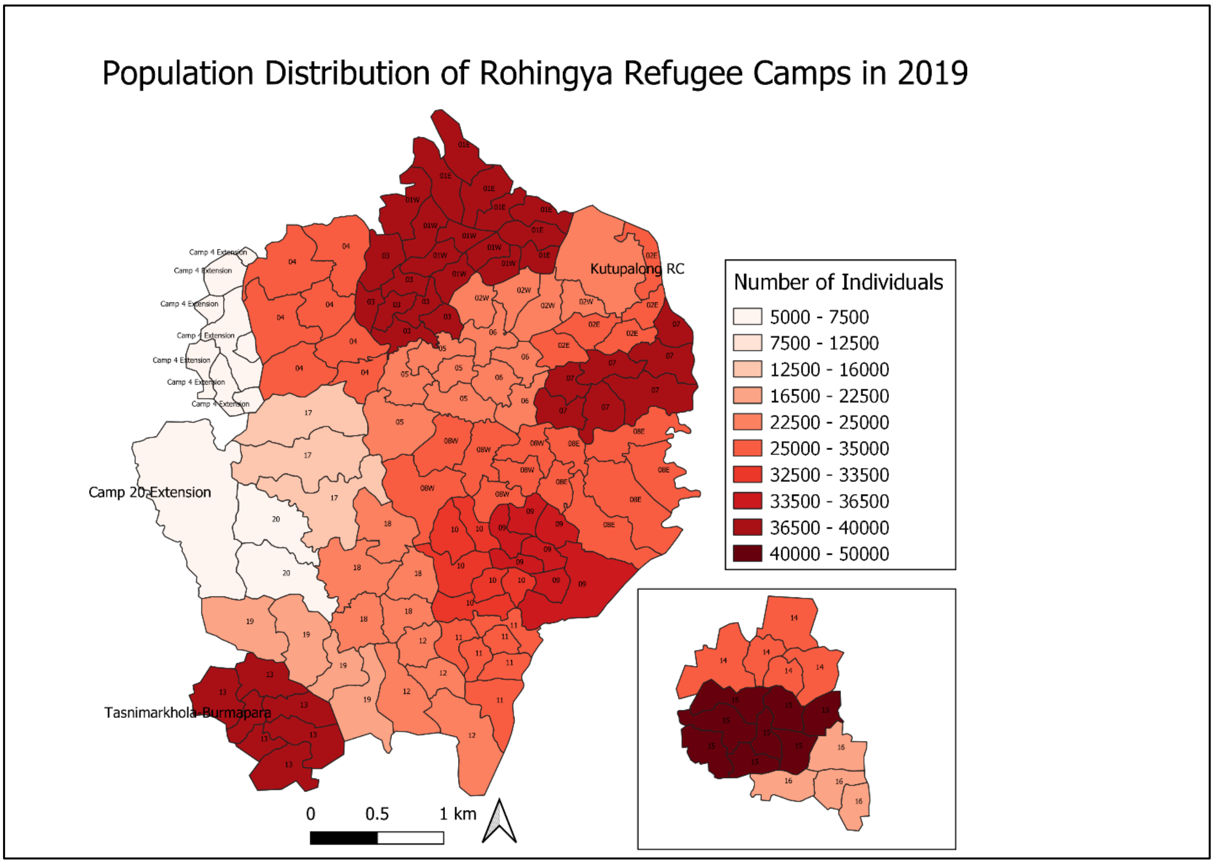


Figure 6 Map showing number of individuals in the refugee camps in 2019. Dataset: UNHCR

The location of healthcare facilities were also plotted on the map to gain an idea of whether their density varies depending on the camp, and to see whether areas that are underserved could be used to measure differences in vulnerability.

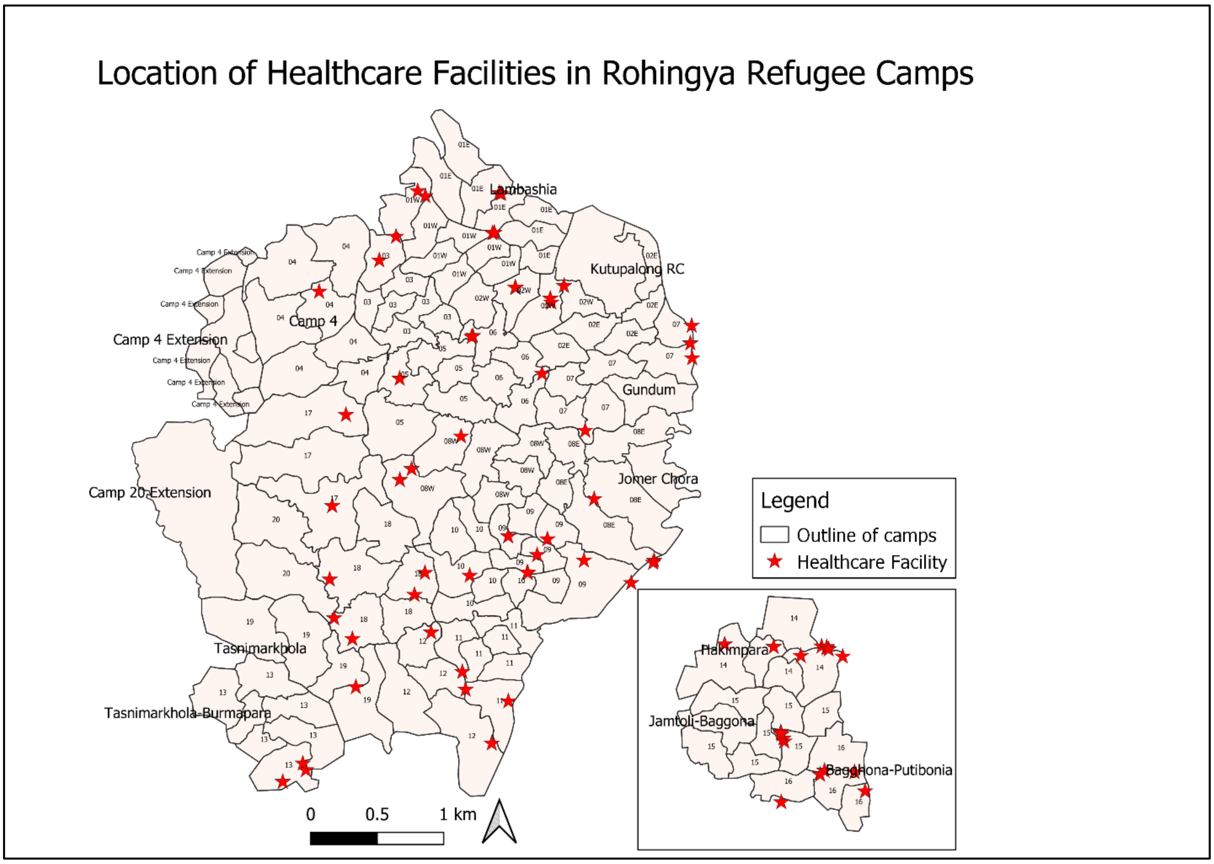
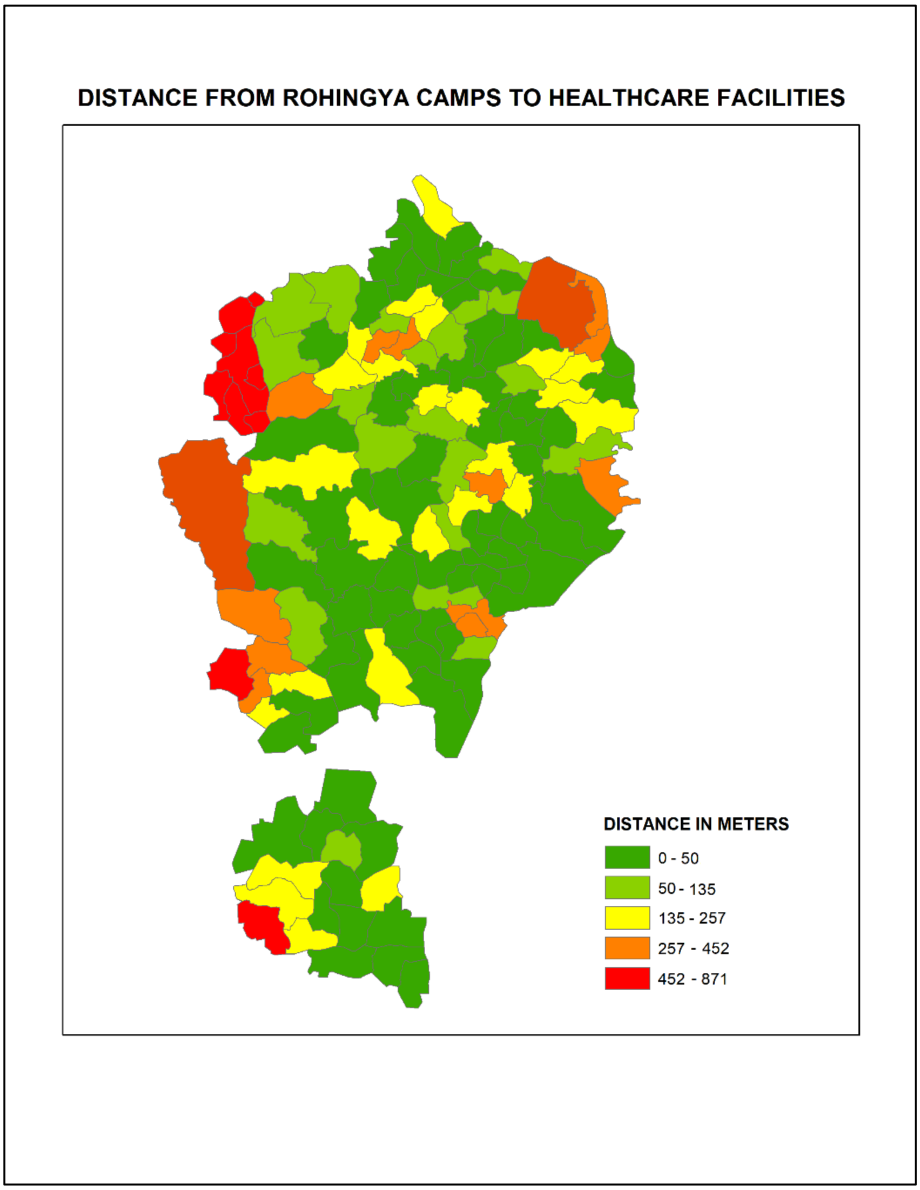


Figure 7 Distribution of healthcare facilities over blocks of the camps. Dataset: REACH Initiative

The location of healthcare facilities were also plotted on the map to gain an idea of whether their density varies depending on the camp, and to see whether areas that are underserved could be used to measure differences in vulnerability. The mean distance from the center point of each polygon to the nearest hospital was then calculated, and the average distances were mapped using ArcGIS to see which parts of the camp were most likely to be underserved by hospitals.

Figure 8 Distance from centroids of Rohingya camps to the nearest healthcare facilities. Dataset: REACH Initiative



4.3. Principal Components Analysis - Correlation

A variance-covariance matrix was considered as the basis for the PCA, which would contain the variances of each variable as well as the covariance associated with all the variable combinations. However, the data collected were from different organizations, and therefore they had different scales and units of measurement, which is why it was not possible to use the variance-covariance matrix. Instead, a correlation matrix was used, which standardizes the data and converts it to a scale where the mean = 0 and variance = 1.

The principal components identified are given in the table below. Information is explained using variance, and the principal components explain 73% of the variance or total variability of the data. Only factors with eigenvalues > 1 are used for the analysis. They are presented in the eigenvalue matrix below (Table 1).

PC	Eigenvalue	%Variance	% Cumulative variance
1	2,6	51,3	51,3
2	1,1	21,7	73,0
3	0,9	18,5	91,5
4	0,4	7,7	99,2
5	0,0	0,8	100,0

Table 1: Eigenvalue matrix

The correlation matrix shows that the principal components 1 and 2 are highly correlated ($r \geq \pm 0.50$) with the five selected variables, which justifies the use of these two components for this data analysis study. The correlation matrix is provided in Table 2.

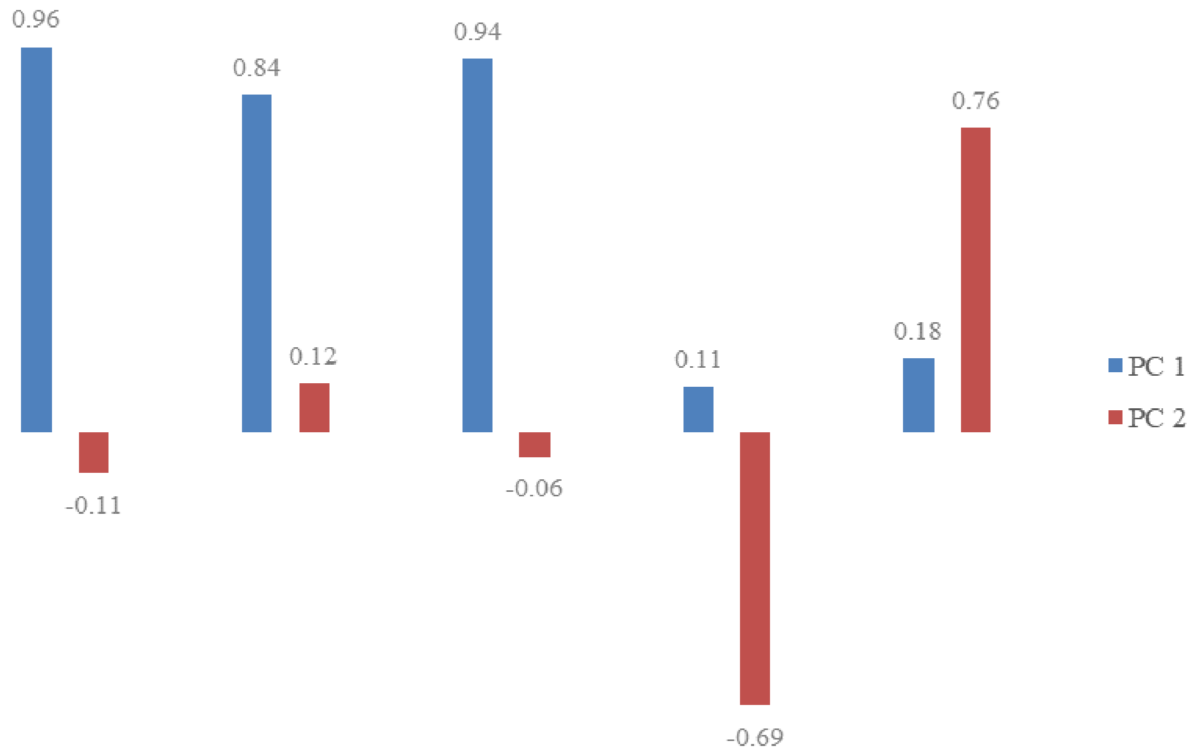
Variables	PC 1	PC 2	PC 3	PC 4	PC 5
Population	0,96	-0,11	-0,11	0,15	-0,15
Number of Latrines	0,84	0,12	0,09	-0,51	0,03
Families with people with specific needs	0,94	-0,06	-0,16	0,28	0,13
Flood Risk %	0,11	-0,69	0,72	0,02	0,01
Landslide %	0,18	0,76	0,61	0,15	-0,01

Table 2: Variable-Component Correlation

The first principal component contains 51.3% of the total variance of the data. Table 2 shows that it is highly positively correlated with the number of individuals (96%), number of latrines (94%) and with the number of families with people with special needs (84%), Camps that will have positive correlation values with this component will have high values for this variable, while those with negative values will have values below the average of the variables highly correlated with this first component.

The second component works in the opposite way. It contains 21.7% of the total variance of the data, and has high correlation values with the two variables related to the natural risks (percentage risk of landslide and percentage risk of flooding). However, these correlations are inverse: with the risk of landslide it is positively correlated (0.76) while with the risk of flooding it is negatively correlated (-0.69), which means that, the percentage risk values of these two natural phenomena act in the opposite way in most of the 34 selected camps. This is because there are camps with percentage values of landslide risk above the average (positive correlation) and, on the other hand, camps with percentage values of flood risk above the average (negative correlation). This is demonstrated in Figure 9.

Figure 9 Correlation of the variables with the first two components



4.4. Principal Components Analysis – Coefficients of Determination

The coefficient of determination **(r^2)** indicates how much variance was provided by each variable to each principal component. This coefficient is expressed in values ranging from 0 to 1, which means it can be converted to percentage values. The r^2 value was obtained by squaring the correlation coefficient of the variables with the component.

Table 1: Coefficients of determination of the principal components 1 and 2

Variables	r^2		% r^2	
	PC 1	**PC 2**	**PC 1**	**PC 2**
Number of individuals	0,93	0,01	93,0	1,1
Number of Latrines	0,71	0,01	71,4	1,4
Families with people with specific needs	0,88	0,00	87,6	0,4
Flood Risk %	0,01	0,47	1,2	47,4
Landslide %	0,03	0,58	3,3	57,9

The results of the coefficient of determination shown in Table 3 indicate that the variables with that contribute the most to the first component are - number of individuals (93%), number of families with people with special needs (87.6%) and number of latrines (71.4%). 70% of this component can be explained by these 3 variables. From this, it can be seen that the first component serves as a measure of the demographic and sanitary conditions in the refugee camps selected in this study.

The second component, on the other hand, contains most of the information on natural variables such as percentage risk of landslide (57.9% of information) and percentage risk of flood (47.4%), The second components measures the natural hazards facing the camp.

4.5. Principal Components Analysis – Biplots

Creating biplots show that the camps with values of the demographic and sanitary variables above the average are located on the right side of the 1st component, while those with values that are below the average of these variables are located on the left side of the component (Figure 10).

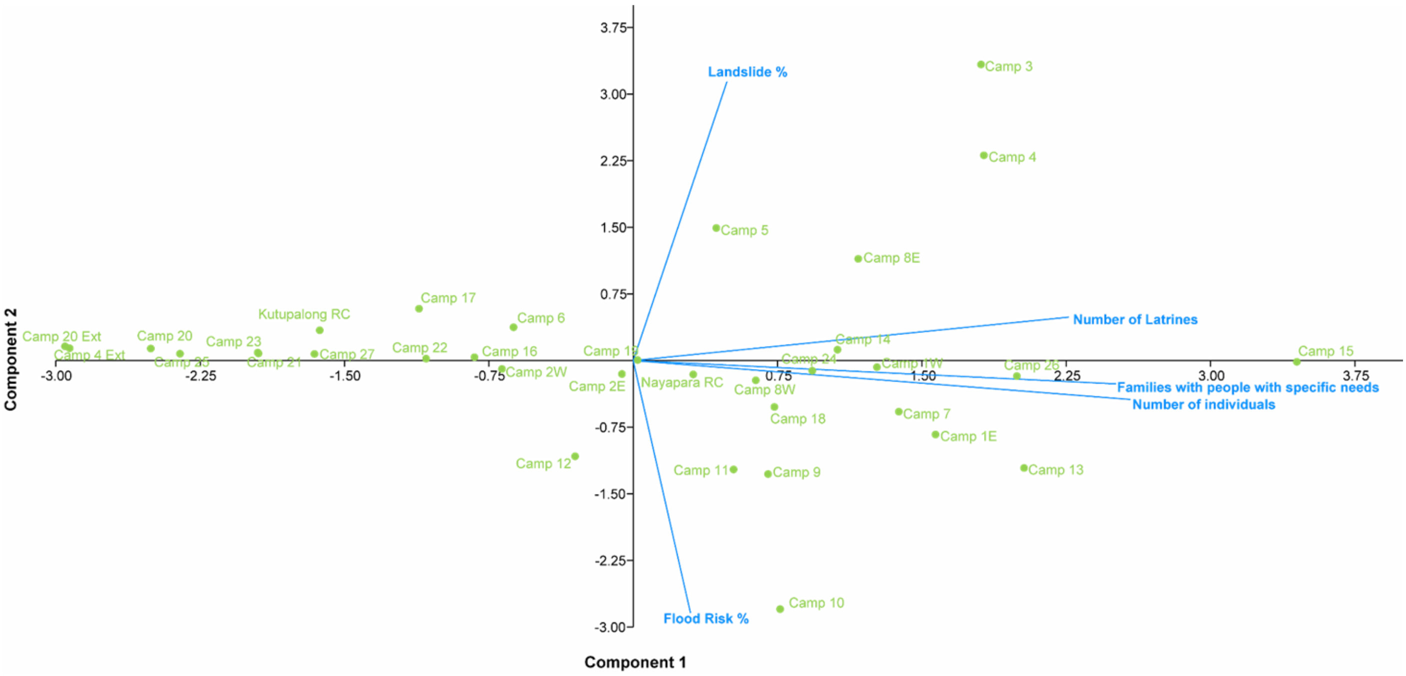


Figure 10 Biplots generated during PCA

Figure 10 shows that high positive correlation (upper right quadrant) with the variable 'percentage risk of landslide' and high negative correlation (lower right quadrant part) with the variable' risk of flooding' are the opposite for most of the camps. In most of the 34 selected camps there are camps with percentage values of landslide above the average in the positive or upper part of the second component, and on the other, camps with percentage flood risk values above the average in the negative segment or lower part of the component.

In general terms, the behavior of the five (5) variables in each of the 34 refugee camps selected is summarized or synthesized by analyzing the first two main components (See Figure 3) as follows:

- The more to the right of the first component (positive sector), the higher from the average the values of the demographic and sanitation variables will be, such as the number of individuals, number of latrines and number of families with people with special needs.
- The more to the left of the first component (negative sector), the lower from the average the values of demographic and sanitation variables will be, such as the number of individuals, number of latrines and number of families with people with special needs.
- The above the second component (positive sector) the higher above the average the values of percentage risk of landslide will be, the opposite occurs with the flood risk values which will be below the average.
- The lower the second component (negative sector), the higher the flood risk percentage values will be from the average, the opposite occurs with the landslide risk values which will be lower than the average.
- The closer to the central point of the components the more similar or close to the average will be the values of the variables.

4.6. Index creation

For the 34 refugee camps, the camp scores of the first two principal components were used due to their high variance and correlation. The index was constructed using these two components and the variables they contain. The scores for these two components were then classified into five intervals based on the natural breaks classification. A numerical scale was then constructed, ranging from 1 to 5, and an alphabetic scale of five codes ranging from the letter “A” to the “E” were constructed. The codes of the numerical scale were then assigned to the intervals of the scores of the first component, taking into account the following premise – the numerical scale designed is inversely related to the scores of the first component, since the highest code of the scale, which is five (5), corresponds to the interval of the values with the lowest below the average of the selected demographic and sanitary variables, while the lowest code, which is one (1), will be assigned to the interval with the highest values above the average of this group of variables.

Codes on the alphabetical scale were assigned to the intervals of the scores of the second component. The highest code, or ‘E’ was assigned to the lowest value in terms of percentage risk of landslide and vice versa, with ‘A’ being assigned to the lower percentage risk of landslide. Once the codes of the two designed scales have been assigned to the two principal component ranges, a final two-digit alphanumeric index is constructed from the union of the assigned codes. This final index describes the demographic and sanitary conditions as well as the percentage risk of landslides and flooding in each of the refugee camps in the area according to data from the United Nations High Commissioner for Refugees (UNHCR) from 2018. The index values are provided in the appendix. The camps were then assigned index. This is presented in the table below.

Table 4: Camps with their assigned index values

Camp Name	PC2 score	PC1 Value	PC2 score	PC2 Value	Index value
Camp 3	1.81	1	3.33	A	1A
Camp 4	1.82	1	2.31	A	1A
Camp 15 (Jamtoli)	3.45	1	-0.01	C	1C

Camp 26 (Nayapara)	1.99	1	-0.17	C	1C
Camp 13	2.03	1	-1.21	D	1D
Camp 8E	1.17	2	1.15	B	2B
Camp 14 (Hakimpara)	1.06	2	0.12	C	2C
Camp 1W	1.27	2	-0.07	C	2C
Camp 24 (Leda)	0.93	2	-0.11	C	2C
Camp 8W	0.64	2	-0.22	C	2C
Camp 18	0.73	2	-0.52	D	2D
Camp 1E	1.57	2	-0.83	D	2D
Camp 7	1.38	2	-0.58	D	2D
Camp 9	0.70	2	-1.28	D	2D
Camp 10	0.76	2	-2.80	E	2E
Camp 5	0.43	3	1.49	B	3B
Camp 19	0.02	3	0.01	C	3C
Camp 2E	-0.06	3	-0.15	C	3C
Nayapara RC	0.31	3	-0.16	C	3C
Camp 11	0.52	3	-1.23	D	3D
Camp 12	-0.30	3	-1.08	D	3D
Camp 16 (Potibonia)	-0.82	4	0.04	C	4C
Camp 17	-1.11	4	0.58	C	4C
Camp 22 (Unchiprang)	-1.08	4	0.02	C	4C
Camp 27 (Jadimura)	-1.66	4	0.07	C	4C
Camp 2W	-0.68	4	-0.09	C	4C

Camp 6	-0.62	4	0.37	C	4C
Kutupalong RC*	-1.63	4	0.34	C	4C
Camp 20	-2.51	5	0.14	C	5C
Camp 20 Ext	-2.95	5	0.16	C	5C
Camp 21 (Chakmarkul)	-1.95	5	0.08	C	5C
Camp 23 (Shamlapur)	-1.95	5	0.09	C	5C
Camp 25 (Ali Khali)	-2.35	5	0.08	C	5C
Camp 4 Ext	-2.93	5	0.14	C	5C

values. This is presented in the table below.

4.7. Land cover change analysis

The software QGIS was used to carry out land cover change analysis. The Semiautomatic Classification Plugin (SCP) was used to carry out the land cover classification. First, training sites or Regions of Interest (ROI) were created using the SCP plugin based on the false color composites. Later, these micro classes were aggregated to form the three land cover classes. The final land cover classification outputs are provided below.

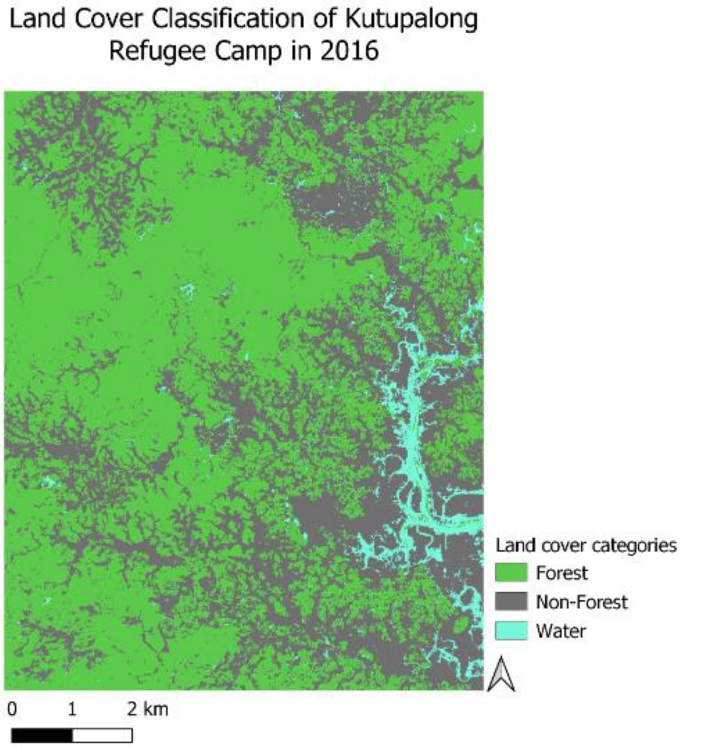


Figure 11 Final land cover classification from 2016 showing the 3 land classes before the refugee influx

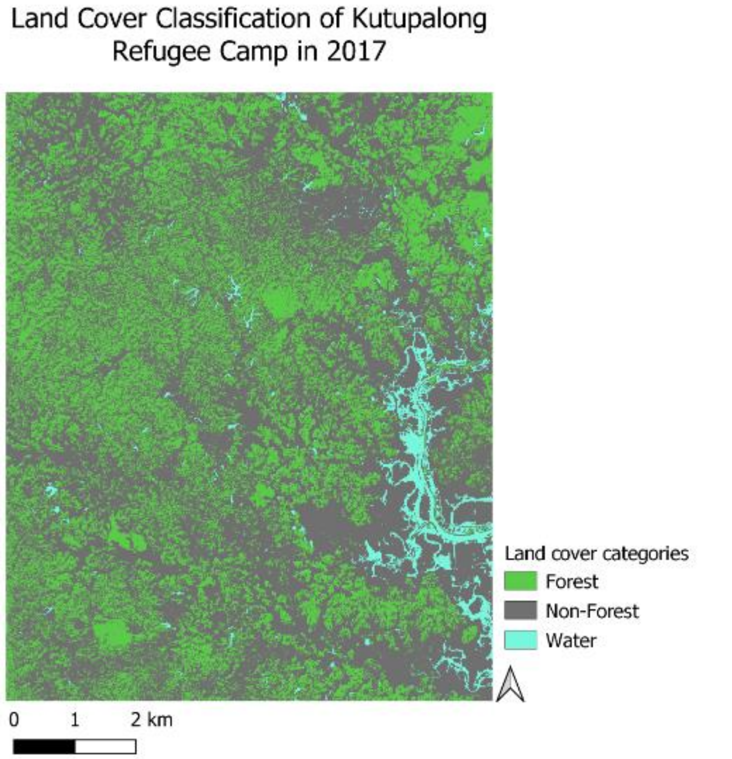


Figure 12 Land cover classes in 2017 showing the expansion of the camp during the refugee influx

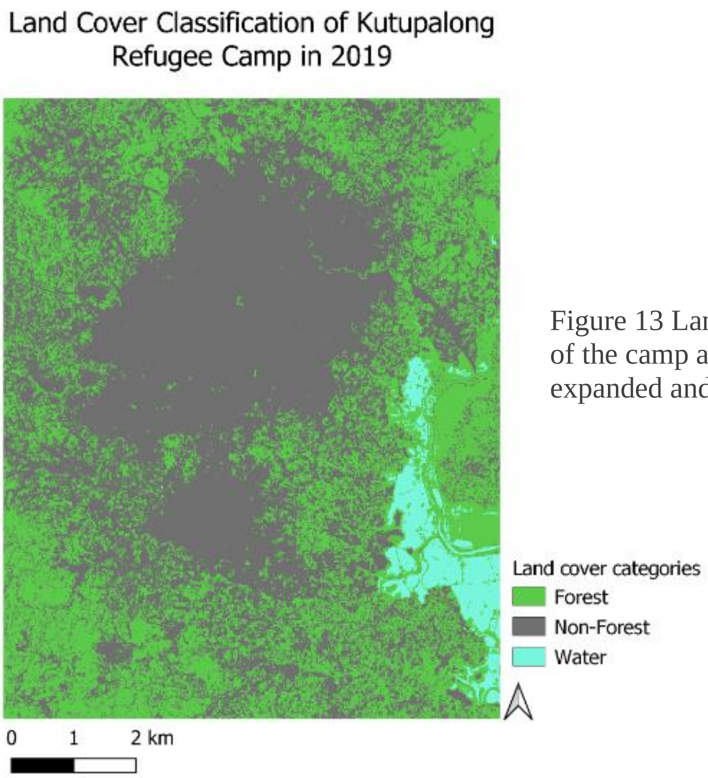


Figure 13 Land cover classes in 2019, showing the expansion of the camp area. The deforested area can be seen to have expanded and the camp has expanded westwards.

The land cover classification shows the expansion of the camp over three time periods. At first, the area was densely forested. The second time period shows increased patchiness in the area, as the first makeshift camps started to be made. In the third time period, the camp is fully established, and the patchiness has shifted to the peripheries. The entire camp area is heavily deforested.

4.8. NDVI calculation

An NDVI was calculated to measure the health of the vegetation by measuring the difference between the NIR and R bands. The vegetation reflects NIR and absorbs R, which is why the NDVI is a standard index used to calculate vegetation health. The negative values of NDVI indicates areas containing water. NDVI is calculated using the following ratio –

(NIR – RED) / (NIR + RED)

The outputs from the NDVI calculation are shown in Figures 14, 15 and 16 below.

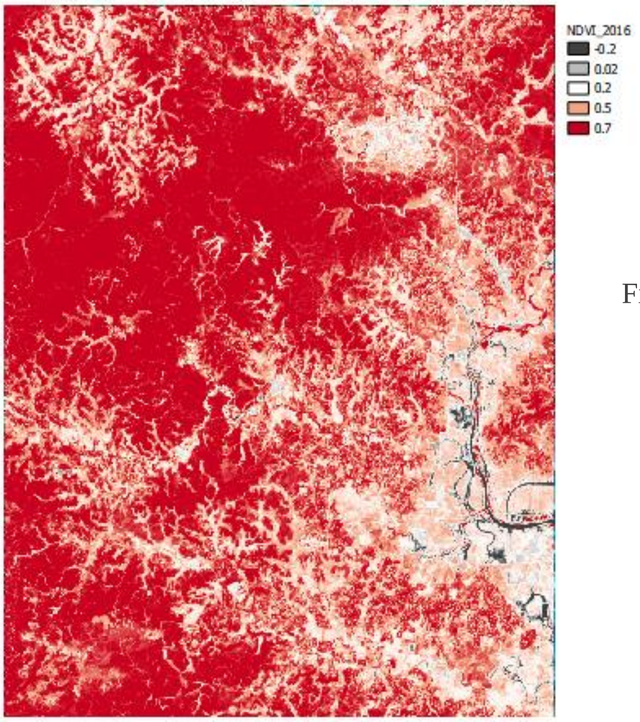


Figure 14 NDVI for 2016 pre-influx vegetation.

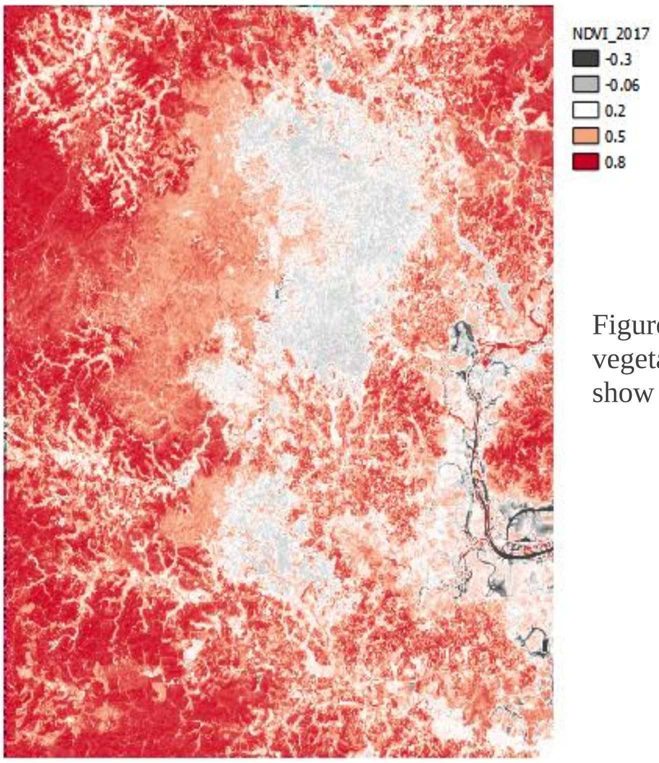


Figure 15 NDVI for 2017 showing the state of the vegetation when the camp was established. Low values show deforestation.

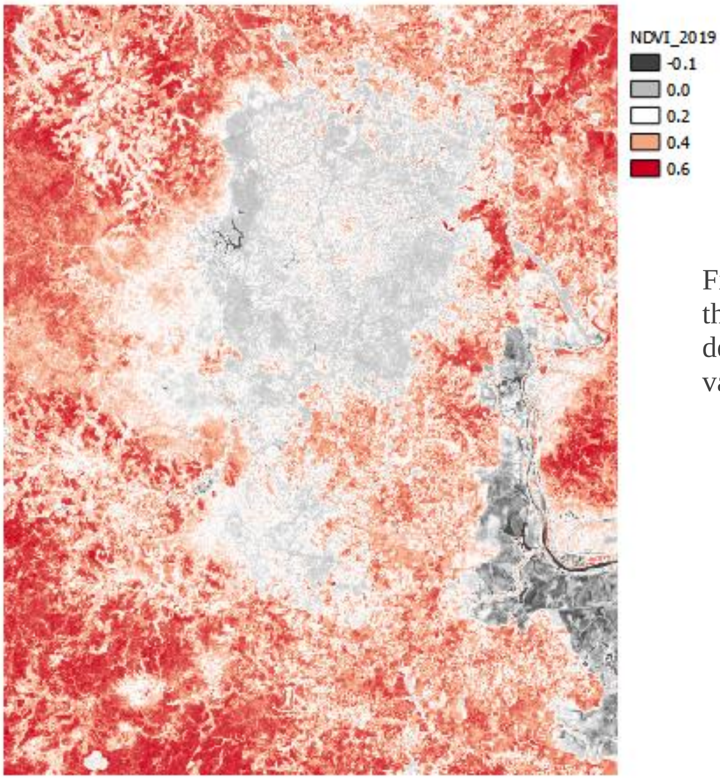


Figure 16 NDVI of 2019 showing the extent of completely deforested land in areas with values of zero.

The land cover classification shows the expansion of the camp over three time periods. At first, the area was densely forested. The second time period shows increased patchiness in the area, as the first makeshift camps started to be made. In the third time period, the camp is fully established, and the patchiness has shifted to the peripheries. The entire camp area is heavily deforested.

4.9. Limitations

The most significant limitations to this research arose from a lack of field data. Time constraints were also a factor as the thesis time period did not allow for data collection in the field. If more data were available, it would have been possible more variables that would make the data analysis more rigorous. However, the index creation model is an example of how even limited data can be utilized for disaster response and planning. The inaccessibility of certain parts of the field were also a limitation that I faced during the study. As the study period was in the rainy season, certain parts of the camp and surrounding areas were flooded and not accessible for ground truth data points collection for validation. I also did not have a chance to include adaptive capacity into the framework of the vulnerability analysis due to a lack of data. The time scale of the refugee crisis being only two years, and repatriation remaining a government policy made it difficult to identify criteria for measuring adaptive capacity.

5. Results and Discussion

This chapter details the overall results and findings of the study. It describes the significance behind the index, providing the results and analysis of the index. It also interprets the spatial images generated, to show how the area has changed since the influx of the refugees.

5.1. Land Change Classification and NDVI

The land change classification showed how the area changed over two time periods. The reference time period was 2016. The second time periods were 2017 and 2019. The satellite images for the first two time periods were captured in November, while the last one was captured in April, which resulted in subtle differences in the land cover analysis such as increased areas of flooding. The three land cover maps were inserted into the SCP land

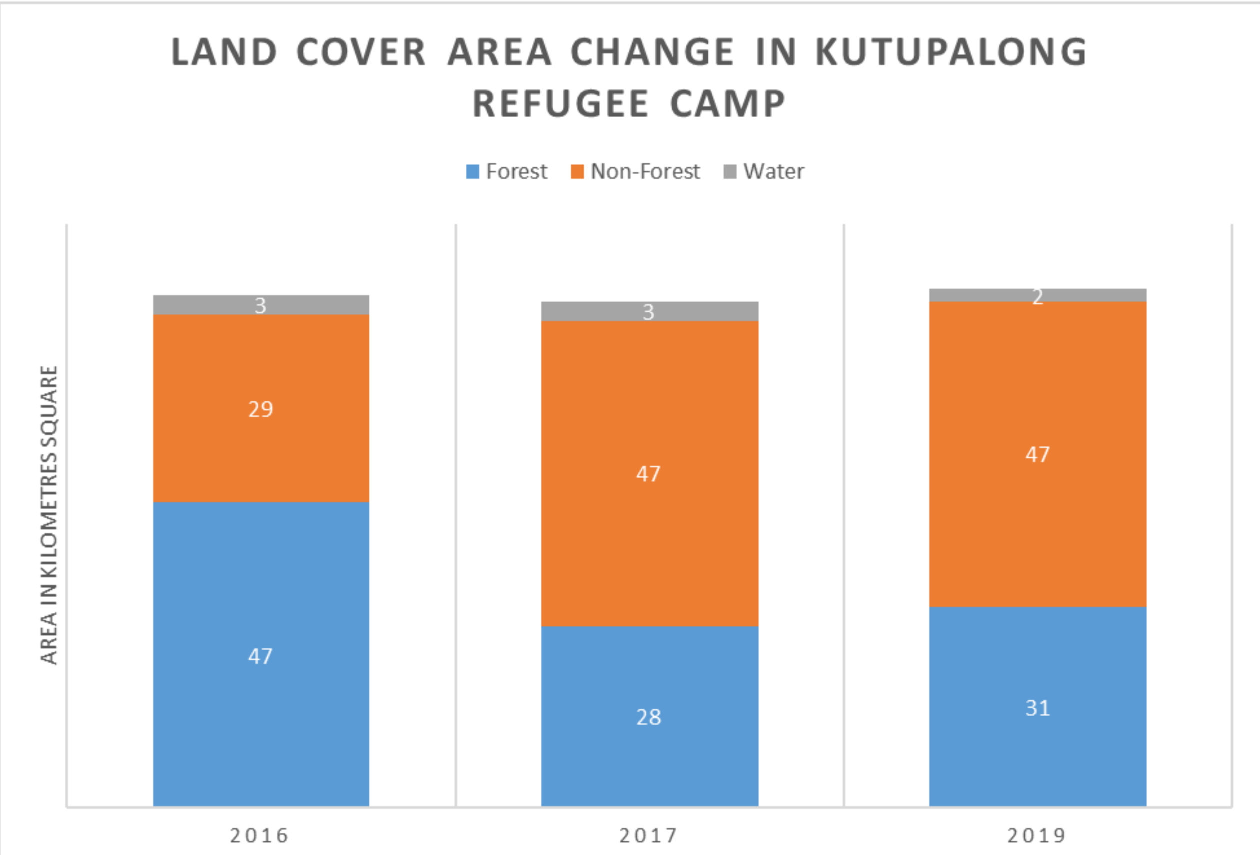


Figure 17 Land cover change in kilometers square

change tool to calculate the amount of pixel change that has occurred from each category. The results are presented in the graphs below.

From these graphs, it can be seen that between 2016 and 2017, each category faced a net change every year. In 2016, forest cover was 47 square kilometers in the camp area. In 2017, forest cover reduced to just 28 square kilometers. This consisted of a 59% reduction in forest cover within the one year of the refugee influx. At the same time, there had been a 62% increase in Non-Forest cover. As both of the satellite images were taken from the same month, this difference cannot be attributed to seasonal changes in vegetation. Between 2017 and 2019, there has been a slight increase in forest cover. This can be attributed to the seasonal difference, as the satellite image has been collected in the month of April, when there is more rainfall, which leads to increased canopy cover. It should also be noted that the river swells during rainfalls, and parts of the Forest or Non-Forest land class has shifted to water. Between 2016 and 2019, the forest cover loss has been a total of 31 square kilometers. The non-forest area has expanded to 47 square kilometers. It is now the largest of the three classes. Previously, forested land was the largest class.

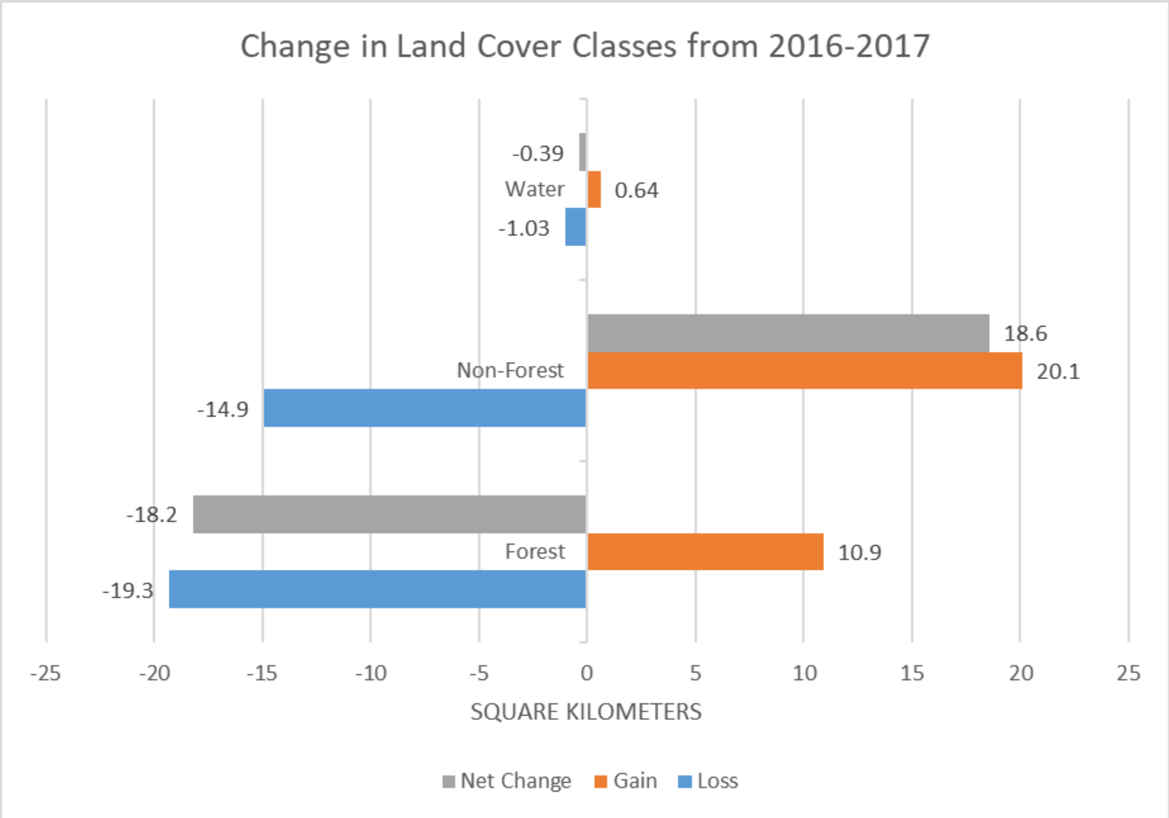


Figure 18 Changing land cover from 2016-2017

The graphs below show that between 2016 and 2017, the Non-Forest Category has had a net change gain of 5.2 square kilometer, and the Forest category has had a net loss of 10.9 square kilometers. From 2017 to 2019, Forest category has had a slight gain of 2.5 square kilometers, while Non-Forest decreased by 2.6 square kilometers.

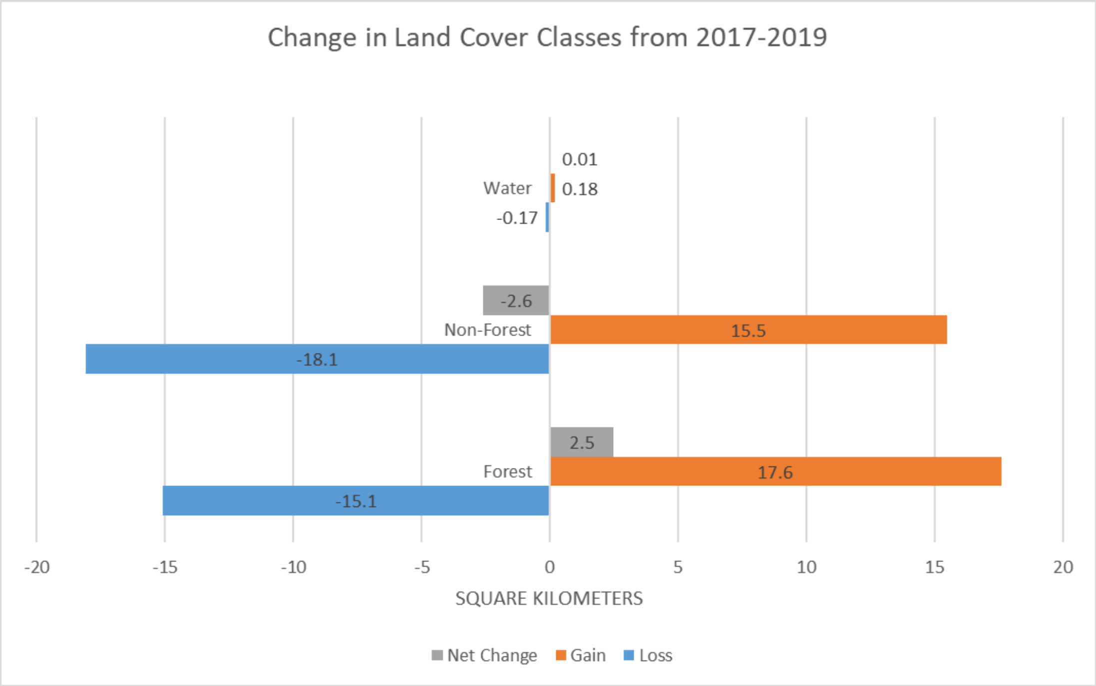


Figure 19 Changing land cover from 2017-2019

Over the three years, the total change in Non-Forest area has seen a gain of 34 square kilometers. The net loss in forest area has been 15 square kilometers. From the land change classification, it becomes clear that the camp has resulted in deforestation in this region. Out of 79 square kilometers of the study area, a total of 47 square kilometers are denuded in 2019. This puts the percentage of non-forest area at 59.4%. Previously, non-forest area occupied 36.7% of the total land area. The forest cover has lost 34% of its pre-influx size. According to the classification outputs, when the refugees first started settling in, the patchiness of the land cover increased. After a year, the camp had transformed into a semi-permanent settlement. The patchiness was filled in as more roads and huts started being constructed.

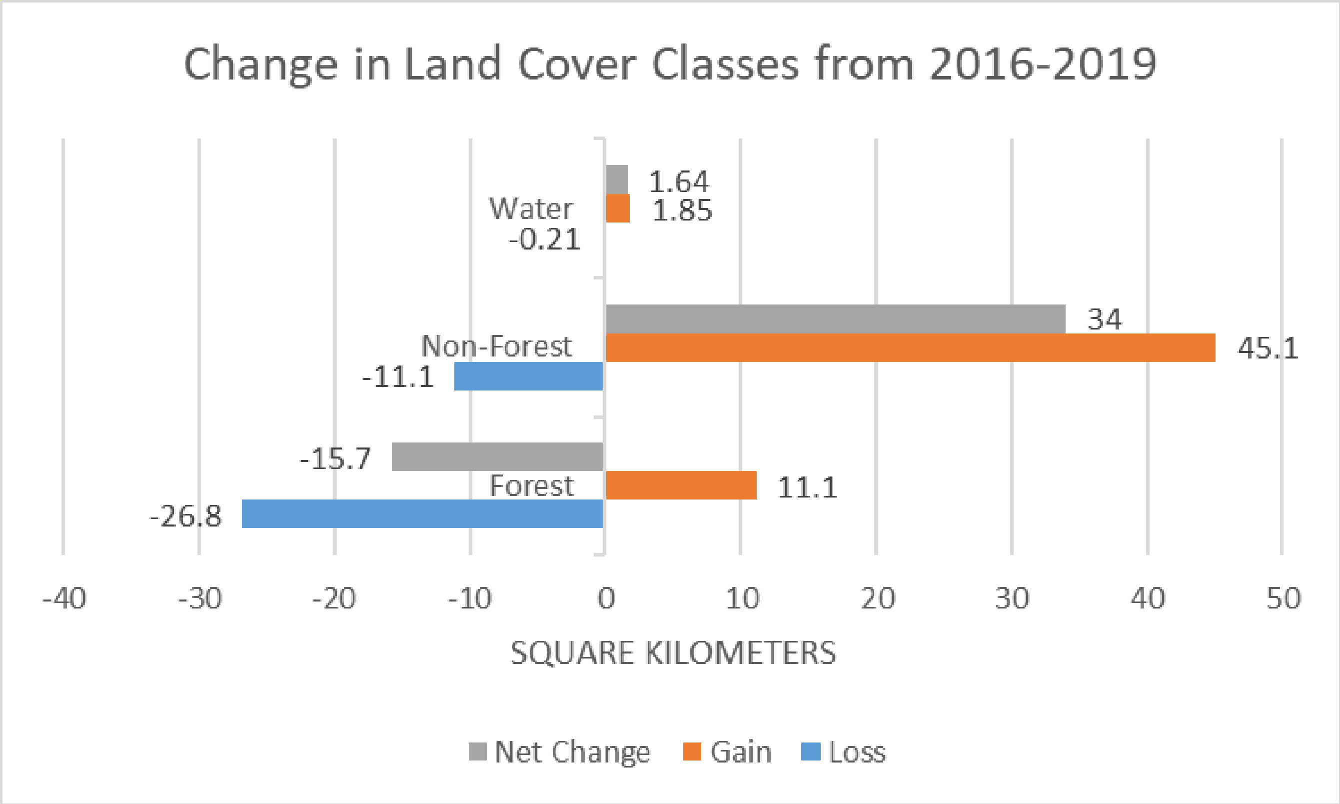


Figure 20 Changing land cover from 2016-2019

To gain a full picture of how the total land cover has changed over time leading to deforestation, it is important to not only look at how many pixels have changed, but also where that change has taken place. The extent of deforestation caused by the encroachment of non-forest areas on forest areas has been mapped for the three time periods. Only the pixel transitions from Forest to Non-Forest were mapped.

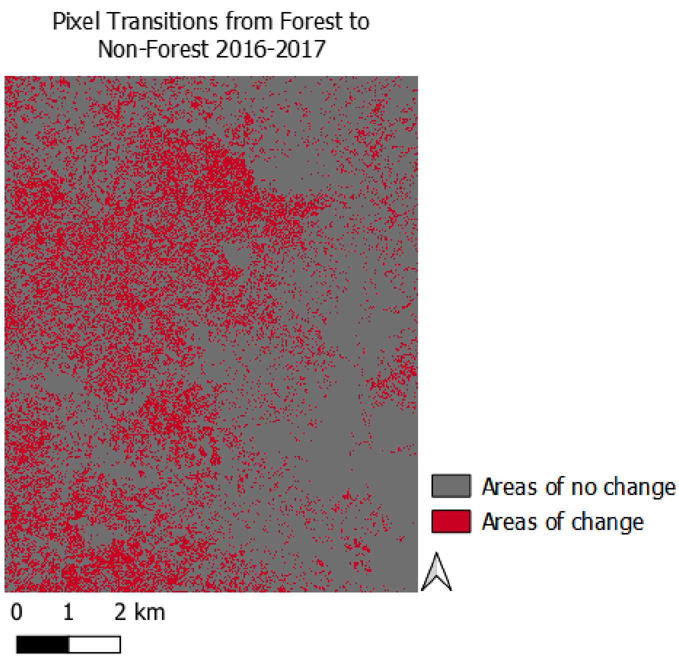


Figure 21 Figure showing where pixel transitions from Forest to Non-Forest occurred from 2016-2017

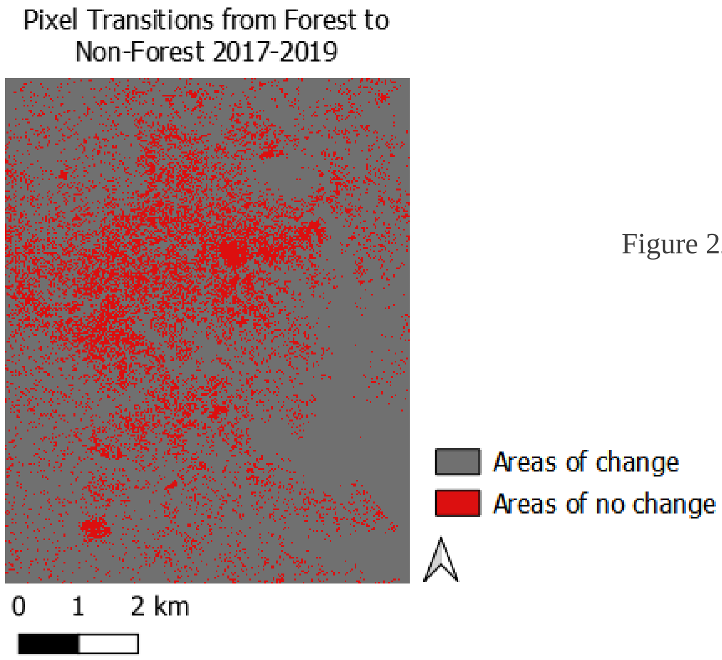


Figure 22 Figure showing where

Between 2016 and 2017, most of the transitions from forest to non-forest occurred where the camp was set up initially. The change was scattered and dispersed, as the camp was not as dense at the time. Most of the pixel transitions happened within the camp area. The initial outline of the Kutupalong refugee camp becomes visible in this image

Between 2017 and 2019, more of the forest area transitioned into camp area. The map of change between 2016 and 2019 shows the total extent of the current refugee camp. From this map, it can be seen that the entire area has now been converted into non-forest. In particular, we can now see the new parts of the camp, such as the Northern and Southern tips.

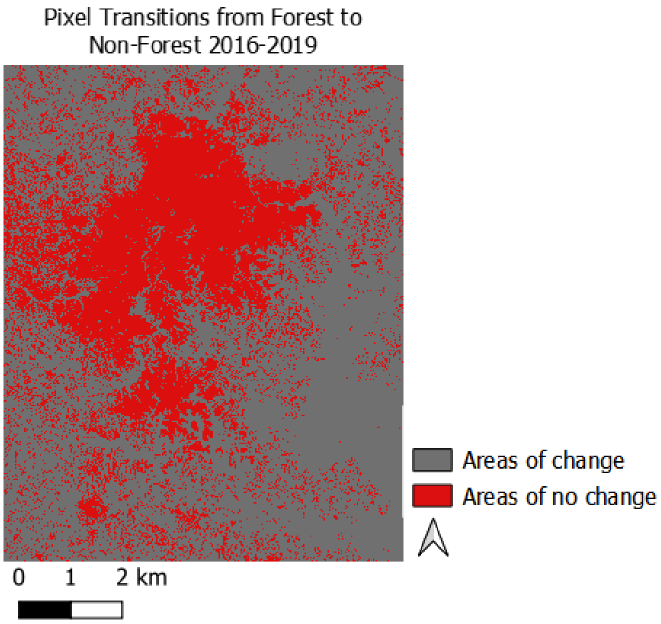


Figure 23 Figure showing where pixel transitions from Forest to Non-Forest occurred from 2016-2017

This loss in forest cover has serious implications for the Rohingya refugee community. Areas that are deforesting are at a greater risk of landslides and flooding as increased deforestation causes soil to run off during the heavy monsoon rains that are prevalent in the area. Without tree roots to compact the soil, the soil runs off and causes landslides. Previous studies have found that deforested areas have landslide deposits up to 3.5 times greater than areas that are forested (de La Fuente 2002). The Rohingya camp is situated in a hilly area, which makes it more prone to landslides due to the slope of the surrounding land. A study conducted in New Zealand over historic time scale has found that deforestation caused thousands of landslides on hilly areas. The changed land use patterns since the arrival of European settlers has contributed to an increase in landslides (Glade 2003).

The NDVI reveals that since the formation of the camp, the forest surrounding the camp has degraded in quality. This likely indicates greater foraging and human disturbance in the area. It could also be the result of the camps becoming a hub of business, due to the influx of international organizations that have boosted local businesses (McKay 2017). Therefore, if steps are not taken to relocate the communities in the areas of the camp which are at the edges of the non-forested area, they are going to be at an increased risk of landslides. This will result in higher rates of mortality and injuries due to landslides and flooding, along with destruction of households.

Loss of forest cover has implications not only for the refugee community, but also for the ecosystem at large. Teknaf and the Chittagong Hill Tracts are rich in ecological diversity, supporting critically endangered bird, insects, reptiles and mammals, including species such as green pigeons, Indian pangolins, Asiatic black bears and leopards (Karim and Ahsan 2016). Deforestation of the forest in the camp and surrounding areas will result in loss of habitat for these species. According to the IUCN in Bangladesh, historic migration routes or corridors of the Asian elephant, considered globally endangered (IUCN 2019), fall within the camps. The loss of forest cover and increase in population due to refugee settlement has meant that the elephant and human conflicts have increased in frequency (Rahman 2019). According to the article, between 2017 and 2018, 6 deaths were the result of elephants trampling humans in their foraging path. The decrease in forest cover will further reduce their foraging area, fragmentation of forests and lead to an increase in human-elephant conflicts, as the animals will be entering more into human territory.

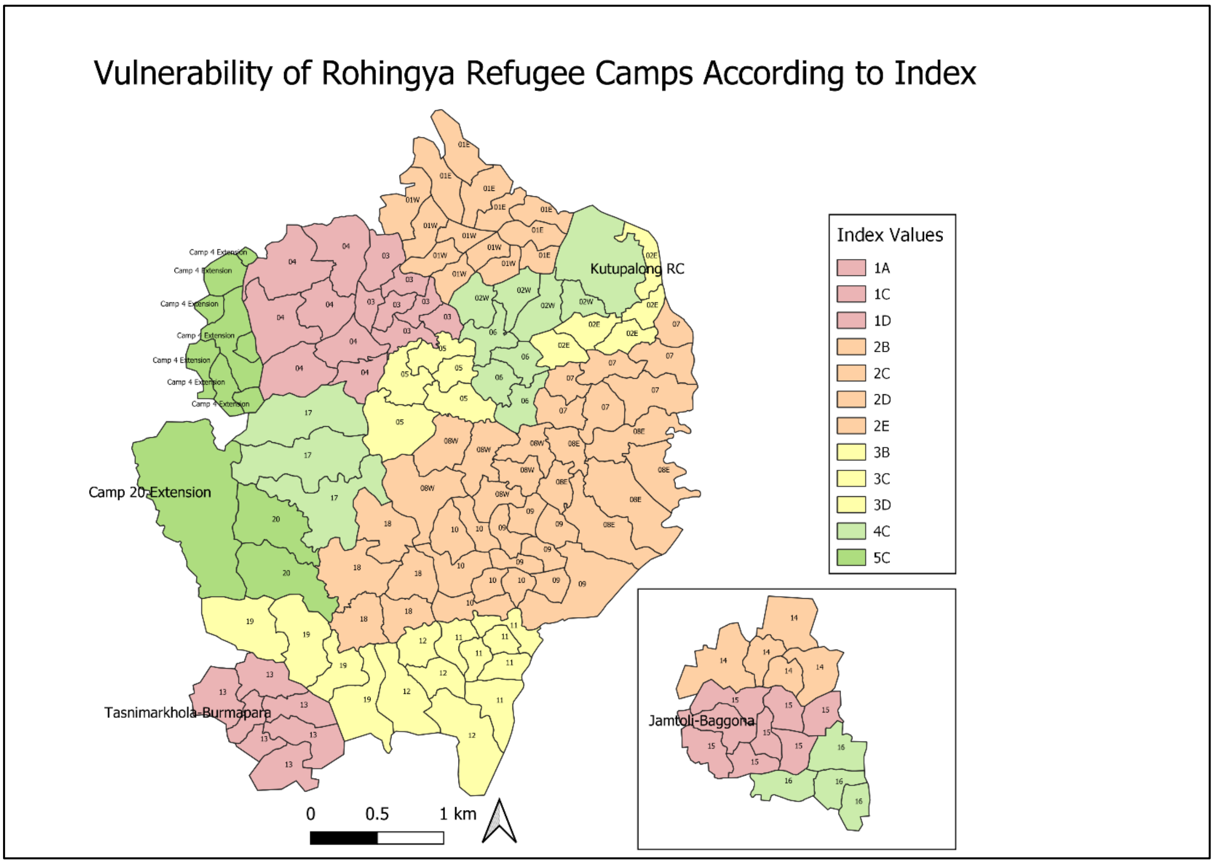
Furthermore, increased deforestation will lead to higher rates of evapotranspiration and surface run offs, which can severely reduce water availability in the region. Water availability is already a growing problem in the area, as the increased concentration of camps and population, and pollution of groundwater has led to a decrease in potable freshwater (Grant 2013). According to the UNHCR, the sudden installation of thousands of tube wells has caused the ground water level to drop rapidly. (Rahman 2019).

A main concern of this area is to ensure that further deforestation does not occur. The integrity of existing forests needs to be protected, and steps need to be taken to prevent these forests from becoming sparse and denuded.

5.2. Index values

The final index generated as a result of the principal components analysis shows the parts of the camps that are more vulnerable. The results indicate that camps 3, 4, 15, 26 and 13 are most vulnerable to environmental disasters, depending on the variables that were considered in this study – population, availability of healthcare and sanitation, and risk of flood and landslide. The camps in the North, those in the East, and South are most vulnerable. The geospatial pattern suggests that the areas that were settled on in the year following the initial migration are most vulnerable to environmental impacts. There could be a number of reasons behind this trend – unavailability of resources and overcrowding due to the increased volume of refugees coming in. The extension sites are less populated, and are less prone to landslide and flood risks. This is likely because of the possibility for increased coordination and planning in the years following the initial crisis due to the intensification of NGO activities in the area. Based on the index results, populations from the most vulnerable blocks of the camps should be moved to the least vulnerable blocks. Families with special needs should be housed in areas of the camp where there are more healthcare and sanitation options available. In cases when this is not possible, efforts should be initiated to set up more healthcare facilities and bathrooms in these areas.

Figure 24 Distribution of healthcare facilities over blocks of the camps. Dataset: REACH Initiative



The index can be used to further coordinate humanitarian response and aid distribution in the largely aid-dependent area, especially in the primary stages of a disaster, when there is dearth of data availability. The population map generated previously shows that certain areas are more densely populated than others. With the help of the vulnerability index, refugee populations can be redistributed based on areas that are less crowded, more resource-rich, and able to absorb a larger number of people. For instance, populations from camps higher 3 and 4 can be resettled in the Camp 4 or Camp 20 extension zones. Using this index, it is also possible to identify which locations are more prone to natural disasters. As the index incorporates populations with special needs, it is possible to carry out the redistribution without having to conduct a separate analysis on healthcare availability. Areas with healthcare facilities which are not at risk of landslide or flooding are automatically included in the index value. The benefit of this index lies in the fact that it is localized, and therefore can be adjusted based on the unique circumstances of the community that the humanitarian response is catering to. For instance, using the principal components analysis, variables such as gender or socioeconomic status could be used in case of coastal communities affected by climate change.

It is important to note that vulnerability maps are highly dependent on the normative assumptions that they are based upon (Abson *et al.* 2012). According to the factors and variables that have been selected, the result of the maps could change. Minor changes within the camp such as redistribution of populations can also alter the results. Therefore, use of the information presented within this study should be context-dependent and necessitates updated analysis. Though a disadvantage of the PCA method of index creation lies in the fact that it cannot be weighted based on the relative importance of the factors on vulnerability. They are all assumed to affect vulnerability in equally, while this may not always be the case in real life applications (Rygel *et al.* 2006). In order to work around this problem, it is recommended that those who will use the index employ their knowledge of the area to enhance the index with qualitative information.

5.3. Policy recommendations

The results of this study reveal that due to the sudden and rapid influx of refugees coming into the area, the growth of the camp has been unplanned and detrimental to the environment. This poses significant risks to the refugee population, host community, and the local ecosystem. In order to ameliorate these effects, the following policy recommendations can be made for the Bangladesh government –

- The Government of Bangladesh should increase coordination with international organizations operating in the area to make use of their analytical resources and spatial datasets for more efficient planning of camp areas and delivery of humanitarian aid, as well as for identifying areas at risk of disease outbreaks.
- The impact of the unplanned expansion of the camp on local forests should be taken into account, so that sustainable forest management practices, including the phasing-out of firewood for cooking are implemented. Household level education must be carried out on sustainable forestry practices.
- The government should increase funding for local forestry services to ensure that illegal logging is prevented. Local foresters should be trained on the specific needs of the refugee community and steps to minimize human-wildlife conflict and game reserve boundaries need to be monitored and protected.
- The Government should ensure that elephant corridors are freed and replantation of trees preferred by elephants on the migratory paths so that elephants can move from one forest patch to another unhindered path, and have sufficient food.
- Currently, a plan is underway to repatriate the refugee population to Bhasan Char, a remote and uninhabited island off the coast of the Bay of Bengal. This move has been widely criticized by international human rights organizations as likely to increase the refugee population’s vulnerability to environmental disasters such as floods and cyclones (McPherson 2019). It is important that the government develops geospatial tools and employs vulnerability indices to analyze the suitability of the area for Rohingya refugees before proceeding with the move.
- Camps located in areas that are more vulnerable to the impacts of environmental disasters should be relocated to areas that are less vulnerable.

- The movement of refugees outside the camp are currently restricted (Human Rights Watch 2019). It is recommended that the free movement of refugees be allowed to neighboring areas that are less vulnerable to environmental impacts.
- Opportunities for income generation as well as sustainable farming should be provided to the refugees in order to improve their adaptive capacity.

There are several international and local organizations working in coordination with government to ensure service and aid delivery for the Rohingyas. Their increased cooperation is necessary to reduce vulnerability in the community. With this view, the following recommendations are made for the NGO's working in the field –

- NGO's should allocate a larger share of their development and aid funds towards mitigating the environmental impacts of the refugee camps, such as by establishing large-scale reforestation, and by providing sources of clean energy.
- They should continue with educational awareness efforts such as the IUCN's elephant awareness program, and should provide communities with the tools to implement sustainable forestry practices.
- NGO's should contribute to reducing environmental risks by establishing knowledge-sharing platforms and working in close cooperation with the government.
- Education programs should be carried out with a particular focus on the health and sanitations needs of individuals with special needs, such as pregnant women, infants and the elderly.
- The UN agencies operating in the field should develop a methodology for vulnerability analysis to be included in their Concept of Operations to ensure that

the Rohingya population does not face increased risks due to the relocation of the camp to Bhasan Char.

6. Conclusions and Future Directions

More than 1.8 million Rohingya refugees from neighboring Myanmar are settled in the Teknaf region of the Chittagong Hill Tracts in Bangladesh. The refugee population residing in these camps are increasingly vulnerable to the impacts of environmental disaster due to a variety of factors, including overcrowding, lack of healthcare and sanitation, and risk of flooding and landslides. The study aimed to develop an environmental vulnerability index of the Rohingya refugee camps based on these factors. Alongside, it looked at the current extent of deforestation in the camp and surround areas. To perform this analysis, two research questions were set -

i) What is the extent of forest cover loss in the refugee camps and surrounding areas?

ii) Are certain areas of the refugee camps more vulnerable than other areas?

In order to answer these questions, a study was conducted in multiple steps. An extensive literature review was performed to gain a thorough theoretical understanding of vulnerability. Studies and reports were surveyed to understand the socioeconomic and biophysical factors affecting the Rohingya population. Based on this understanding, an environmental vulnerability index was calculated using a principal components method. A PCA based vulnerability index was calculated to gain an aggregate understanding of which areas are at risk. The data for developing the index was gathered through secondary sources, including international organizations operating in the area, such UNHCR, Reach Initiative, ISCG, and WASH. The analysis was supplemented by land cover analysis to quantify deforestation between three time periods, 2016 (the pre-influx, or reference time period), 2017 (a year after the camp was established) and 201 (present day). Open source satellite data from the Sentinel satellite at 10m resolution was obtained from the USGS Earth Explorer website, and based on this, the land cover was classified using a maximum likelihood classification using the QGIS software into three categories – Forest, Non-forest and Water. NDVIs were also developed for the three time periods to measure the health of the forest cover. Site visits were carried out at 15 locations inside the camp to verify the accuracy of the land cover classification.

The results of the index showed that certain parts of the camp are more vulnerable to environmental disasters than other parts. The index was ranked from 1A to 5C, with camps ranked 1 being the most vulnerable, and camps ranked 5 being the least vulnerable. The results showed that camps 3, 4, 15, 26 and 13 are the most vulnerable camps. These are located at the Northeastern and Southeastern boundaries of the camp. The least vulnerable camps were camps 2 West, Kutupalong RC, 20, 20 Extension 21, 23, 25 and 4 Extension. The results suggest that steps need to be taken to intensify aid efforts in these areas and to relocate people to less vulnerable areas. The land cover analysis revealed that over three years, Non-Forest area increased by 34 square kilometers. The net loss in Forest area has been 15 square kilometers. In 2019, the percentage of non-forest area stands at 59.4%, while it was 36.7% of the total land area in 2016. The forest cover has decreased by 34%, and stands at 39.7% of the total land area, while before the refugee influx it used to occupy 60% of the total land area.

This carries serious consequences for the increased vulnerability of the host and refugee populations, as deforestation increases the risk of landslides due to rainfall and flooding. Deforestation also has negative impacts on the local ecosystem. Habitat loss will also directly affect the refugee population by increasing frequency of human-wildlife conflict. In the future, due to the camp's detrimental effects on forest cover, the remaining forest area risks becoming deforested. Steps need to be taken to prevent this from happening, such as the implementation of forest management practices and monitoring tools. A series of recommendations for the Government of Bangladesh and the NGOs operating in the camps were outlined based on these findings.

The study shows that PCA-based indices, combined with geospatial technologies for land cover analysis are effective in analyzing environmental vulnerability in a small, localized context to better deliver humanitarian aid. In the future, a more detailed study should be conducted based on data collected from the field. Variables such as gender, sources of energy, number of access roads and numbers of human-animal conflicts by camp should be taken into account for the principal components analysis. Economic impacts of the camp on the host community can also be studied by gathering population level data on incomes, prices of food and necessities, and cost of accommodation, and mapping them spatially. The environmental impacts of the camp should be studied in depth from a number of perspectives, such as by using remotely sensed nigh time imagery to analyze the impact of night time lights on wildlife. Environmental effects of non-recycle single use plastic aid products should also be taken studied by mapping landfill sites and their nearness to groundwater sources or streams.

Future studies should aim to include adaptive capacity to measure vulnerability by including variables such as education level, long-term development plans, and the impacts of government policies. In the past year, the GoB has tightened its scrutiny of the Rohingya community by enacting policies that have been thought to further increase vulnerability among the camp's inhabitants. This includes policies such as the cessation of mobile telecommunication networks in the camp area, curbing of certain NGO's working in the area, and increasing police presence in the surrounding areas which has led to violence

(Chowdhury 2019). The inclusion of the effects of qualitative policies such as these would improve the understanding of vulnerability within the camp.

Overall, both principal components analysis and remote sensing based on satellite imagery are found to be extremely important tools for monitoring and responding to environmental problems caused by migration that also impact refugee populations. As the world starts to see increases in climate induced migration, these tools will become essential in crisis response and management.

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Software used

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QGIS 3.8.3. QGIS Development Team. Open Source Geospatial Foundation Project.

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Appendix I. Ground truth points used for map accuracy verification

Point	Lat/Long	Description	Photo
1	21.12’38”N 92.09’51”E	Non-forest	
2	21.11’25”N 92.09’01”E	Non-forest	
3	21.09’35”N 92.08’37”E	Non-forest	
4	21.09’05”N 92.07’51”E	Forest	
5	21.10’03”N 92.09’29”E	Forest	

6	21.12’49”N 92.10’55”E	Forest	
7	21.11’30”N 92.10’16”E	Water	
8	21.12’00”N 92.09’55”E	Water	
9	21.11’59”N 92.09’48”E	Water	

Appendix II. Pixel transitions from 2016-2017

ChangeCode	ReferenceClass	NewClass	PixelSum
1	1.0	1.0	65763320
2	1.0	2.0	13005462
3	1.0	3.0	3726442
4	2.0	1.0	4803728
5	2.0	2.0	20545192
6	2.0	3.0	4801802
7	3.0	1.0	16639
8	3.0	2.0	521310
9	3.0	3.0	7376505

Appendix III. Pixel transitions from 2017-2019

ChangeCode	ReferenceClass	NewClass	PixelSum
1	1.0	1.0	61672977
2	1.0	2.0	8905148
3	1.0	3.0	5562
4	2.0	1.0	22552482
5	2.0	2.0	11339774
6	2.0	3.0	179708
7	3.0	1.0	4098519
8	3.0	2.0	309304
9	3.0	3.0	11496926

Appendix IV. Pixel transitions from 2016-2019

ChangeCode	ReferenceClass	NewClass	PixelSum
1	1.0	1.0	70096566
2	1.0	2.0	10729138
3	1.0	3.0	1669520
4	2.0	1.0	16343412
5	2.0	2.0	9625122
6	2.0	3.0	4182188
7	3.0	1.0	1884000
8	3.0	2.0	199966
9	3.0	3.0	5830488

Appendix V. Scores by camps of the first two principal components

Camp name	Scores	
	PC 1	PC 2
Camp 1E	1,571	-0,833
Camp 1W	1,267	-0,075
Camp 2E	-0,059	-0,151
Camp 2W	-0,682	-0,095
Camp 3	1,808	3,333
Camp 4	1,822	2,311
Camp 4 Ext	-2,929	0,138
Camp 5	0,432	1,492
Camp 6	-0,622	0,374
Camp 7	1,380	-0,575
Camp 8E	1,169	1,145
Camp 8W	0,637	-0,222
Camp 9	0,701	-1,278
Camp 10	0,763	-2,798
Camp 11	0,521	-1,226
Camp 12	-0,302	-1,078
Camp 13	2,031	-1,210

Camp name	Scores	
	PC 1	PC 2
Camp 14	1,062	0,123
Camp 15	3,449	-0,015
Camp 16	-0,825	0,037
Camp 17	-1,113	0,584
Camp 18	0,734	-0,522
Camp 19	0,023	0,006
Camp 20	-2,507	0,135
Camp 20 Ext	-2,953	0,160
Camp 21	-1,947	0,080
Camp 22	-1,076	0,021
Camp 23	-1,951	0,090
Camp 24	0,930	-0,114
Camp 25	-2,355	0,077
Camp 26	1,994	-0,175
Camp 27	-1,657	0,074
Kutupalong RC	-1,629	0,341
Nayapara RC	0,312	-0,156

Appendix VI. Description of the behavior of the variables highly correlated with the first component, range of values of the scores and codes of the numerical scale assigned to each interval

Variables description	Scores interval	Numeric code
Number of individuals, latrines and families with people with special needs well below the average of the variables.	(-2,95) to (-1,95)	5
Number of individuals, latrines and families with special needs below average.	(-1,94) to (-0,62)	4
Number of individuals, latrines and families with people with special needs very close to the average of the variables.	(-0,61) to (0,52)	3
Number of individuals, latrines and families with people with special needs above the average of the variables.	(0,53) to (1,57)	2
Number of individuals, latrines and families with people with special needs well above the average of the variables.	(1,58) to (3,45)	1

Appendix VII. Description of the behavior of the variables highly correlated with the second component, range of values of the scores and codes of the alphabetic scale assigned to each interval

Variables description	Scores interval	Alphabetic code
Percent flood risk values well above the average and percentage landslide risk values well below the average.	(-2,80)	E
Percent flood risk values above the average and percentage landslide risk values below the average.	(-2,79) to (-0,52)	D
Percent of flood and landslide risk values very close to average	(-0,51) to (0,58)	C
Percent landslide risk values above the average and percentage flood risk values below the average.	(0,59) to (1,49)	B
Percent landslide risk values well above the average and percentage flood risk values well below the average.	(1,50) to (3,33)	A

Appendix VIII. UNHCR dataset containing block level population data

Camp	Block	Families with Separated Children	Families with unaccompanied children	Families with a person with disability	Families with older person at risk	Families with Older person at risk with children	Families with people with serious medical condition	Single male parent with infants	Single female parent	Families with people with specific needs
Camp 10 Total		**128**	**80**	**382**	**342**	**244**	**512**	**94**	**1,065**	**2,436**
Camp 11 Total		169	62	267	297	158	238	65	1,083	1,979
Camp 12 Total		88	35	160	235	112	155	35	832	1,465
Camp 13 Total		244	79	314	398	218	350	70	1,449	2,805
Camp 14 Total		121	45	187	319	143	308	43	1,014	1,912
Camp 15 Total		235	59	354	590	200	465	63	1,617	3,211
Camp 16 Total		92	23	171	206	83	164	37	721	1,341
Camp 17 Total		108	22	144	158	82	126	41	722	1,247
Camp 18 Total		152	62	239	222	170	294	82	1,137	2,081
Camp 19 Total		123	33	190	222	82	119	47	765	1,418
Camp 1E Total		175	45	556	466	327	490	57	1,175	2,951
Camp 1W Total		167	32	406	450	216	446	66	1,277	2,773
Camp 20 Total		27	12	95	70	48	77	20	305	571
Camp 20 Extension Total		26	14	48	38	25	47	12	164	316
Camp 21 Total		66	23	109	96	32	105	35	521	903
Camp 22 Total		69	17	161	156	77	154	16	586	1,120
Camp 23 Total		48	12	71	95	42	65	10	710	969
Camp 24 Total		177	73	299	285	121	256	43	1,637	2,632
Camp 25 Total		38	23	75	83	33	87	18	493	754
Camp 26 Total		170	53	280	357	113	215	81	2,179	3,234
Camp 27 Total		54	13	99	88	33	63	21	731	1,025
Camp 2E Total		163	54	269	254	208	312	55	1,259	2,275
Camp 2W Total		111	17	291	244	117	269	59	834	1,756
Camp 3 Total		200	61	375	367	288	320	64	1,433	2,685
Camp 4 Total		247	91	204	302	207	295	101	1,512	2,590
Camp 4 Extension Total		24	14	57	41	36	55	17	214	406
Camp 5 Total		158	68	214	296	163	215	61	1,097	1,965
Camp 6 Total		164	44	213	245	131	316	42	836	1,845
Camp 7 Total		225	28	365	377	245	464	106	1,312	2,833
Camp 8E Total		152	69	338	364	239	414	83	1,061	2,317
Camp 8W Total		95	36	235	269	149	295	80	746	1,686
Camp 9 Total		151	73	387	402	263	494	96	1,083	2,538
Kutupalong RC Total		52	17	344	86	35	772	7	534	1,519
Nayapara RC Total		176	41	607	164	50	1,197	36	1,185	2,816
No camp Total		23	8	41	60	17	34	20	264	448

Appendix IX. REACH Initiative data containing health and sanitation information

Camp Name	Number of families (UNHCR population data as of 30 September 2018)	Number of individuals (UNHCR population data as of 30 September 2018)	Number of shelters (based on StreetMap Export as of 30 October 2018)	# of shelters with at least one functional and ... latrine block within 50m	% shelters with at least one functional and ... latrine block within 50m	# of shelters with at least one functional improved water source within 200m	% shelters with at least one functional improved water source within 200m	# functional improved water sources with ... latrine within 10m
Camp 02W	5,748	25,130	4,684	4,652	99%	4,684	100%	198
Camp 03	9,021	38,810	7,031	7,031	100%	7,031	100%	283
Camp 04	7,531	30,600	7,894	7,869	100%	7,894	100%	449
Camp 04 Ext	1,046	4,328	819	808	99%	819	100%	40
Camp 05	6,028	25,075	6,641	6,628	100%	6,641	100%	308
Camp 06	5,721	24,564	4,919	4,903	100%	4,919	100%	255
Camp 07	9,156	38,488	7,521	7,158	95%	7,521	100%	425
Camp 08E	7,291	31,624	8,077	7,602	94%	8,077	100%	393
Camp 08W	7,519	32,672	7,923	7,899	100%	7,923	100%	391
Camp 09	8,601	36,475	6,983	6,931	99%	6,983	100%	602
Camp 10	7,575	32,667	7,526	7,520	100%	7,526	100%	757
Camp 11	7,069	31,164	6,837	6,817	100%	6,837	100%	565
Camp 12	4,905	22,136	4,953	4,947	100%	4,953	100%	442
Camp 13	9,618	41,056	7,706	7,648	99%	7,706	100%	402
Camp 14 (Hakim	6,904	31,357	7,553	7,539	100%	7,553	100%	221
Camp 15 (Jamto	11,174	49,442	11,783	11,768	100%	11,783	100%	315
Camp 16 (Potibc	4,839	21,639	5,017	4,954	99%	5,017	100%	192
Camp 17	3,649	15,472	3,840	3,827	100%	3,840	100%	327
Camp 18	6,655	27,220	7,635	7,597	100%	7,635	100%	361
Camp 19	4,816	20,852	3,932	3,929	100%	3,932	100%	424
Camp 20	1,735	7,180	1,797	1,787	99%	1,797	100%	106
Camp 20 Ext	976	3,992	558	538	96%	558	100%	38
Camp 21 (Chakm	3,011	12,281	2,350	2,350	100%	2,350	100%	119
Camp 22 (Unchip	4,583	22,206	3,876	3,808	98%	3,876	100%	61
Camp 23 (Shaml	2,672	11,012	1,694	1,088	64%	1,641	97%	381
Camp 24 (Leda)	7,800	33,714	3,900	3,670	94%	3,855	99%	94
Camp 25 (Ali Kh	2,183	9,697	1,928	1,681	87%	1,906	99%	63
Camp 26 (Nayap	9,493	41,475	6,521	6,158	94%	6,521	100%	143
Camp 27 (Jadim	3,172	14,354	3,243	2,800	86%	3,236	100%	97
Kutupalong RC*	3,786	19,007	3,708	1,770	48%	3,442	93%	54
Nayapara RC	5,732	27,032	781	757	97%	781	100%	48
All Camps	205,386	891,564	176,131	170,574	97%	####	100%	10,234

* Only partially assessed due to security concerns