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HUMANITARIAN SATELLITES

A REMOTE SENSING APPROACH TO BUILT-UP AREA ESTIMATION IN REFUGEE CAMPS

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Humanitarian Satellites: A remote sensing approach to built-up area estimation in refugee camps.
Humanitära satelliter: En fjärranalysmetod för att estimera arean byggnader i flyktingläger.

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ABSTRACT

The determination of the built-up area of a refugee camp is an important task as it can be used for estimating the population. While high resolution satellite imagery can be costly, since 2015 Sentinel-2 data has become available through the European Space Agency. Sentinel-2 offers 10 m resolution images with frequents updates. In this paper three methodologies are compared for the purpose of estimating built-up area using Sentinel-2 imagery: Index Based (using the IBI); Supervised classification; and Digitization. The study areas chosen for this study are Nyarugusu Refugee Camp, in Tanzania, and Kutupalong Refugee Camp, in Bangladesh. Of the three methodologies the Digitization offers the best in the accuracy analysis, followed by the Supervised Classification and, finally, the Index Based Method. Yet, the other two methodologies could still find some specific application such as the delineation of small features. Furthermore, the three methodologies are used in creating a time series analysis to investigate their potentials to track the development of the built-up area of a refugee camp. The built-up area is then correlated to the population of the camp. Once again, the Digitization Method proves itself to be the most accurate of the three methodologies explored.

TABLE OF CONTENTS

1 INTRODUCTION

In the wake of global conflict, raising intolerance and encroaching climate change, millions of people every year find themselves forced to leave their homes and seek refuge in camps for internally displaced persons (IDP camps) and refugee camps. An estimated 68.5 million people are currently forcibly displaced worldwide (UNHCR 2019b); if it was a country, it would be the 20th largest country by population, a population bigger than that of France(Wikipedia 2019c).

1.1 BACKGROUND

In the complex scenario of a refugee camp, accurate and quick estimation of the population is essential to aid the relief operations. Unfortunately, the already large amount of people entering and leaving a camp on a daily basis is often put even more under stress by sudden influxes of people as a result of political, economic or social unrests. To further aggravate the problem, refugee and IDP camps are often located in countries of the Global South (UNHCR 2016a) and the resources allocated to humanitarian operations are often limited, if not, scarce. To combat this matter, a rapid assessment of the population can be performed by measuring the population of sample areas within the camp to later estimate it for the whole camp(Brown et al. 2001); these estimations are often relying on remotely sensed data. In a study from (Füreder et al. 2014)the number of dwellings is extracted by automatically identifying single objects, a process called an object-based image analysis (OBIA), using very high resolution (VHR) imagery. While certainly allowing for greater accuracy, up to date VHR imagery is often costly, ranging in the thousands of euros, for minimum orders of 100 km^2 (LANDinfo 2019).

While performing OBIA requires high resolution imagery, estimation of the built-up area can be performed using lower resolution images. In recent years an increasing amount of open source remote sensing data has been made available by various national and international space agencies. First among them, the Sentinel-2 satellite program from the European Space Agency (ESA) provides free to download world coverage multiband, medium resolution data every few days. While a step forwards, the relatively low resolution of Sentinel-2 is too coarse for OBIA extraction of single dwellings in a refugee camp. Nevertheless, estimations of the built-up area are feasible; this is also thanks to the multispectral characteristics of the image, allowing the use of False Color Composition (FCC) as a way to highlight vegetation. A study from Wendt et al. (2017) not only demonstrated how Sentinel 2 data can be used effectively to digitize built-up area in a refugee camp, but also how, in some cases, the built-up area is a better proxy for the population than the number of dwellings, as the latter varies quickly as the inhabitants tend to build non-inhabited structures, like kitchens and toilets. These findings shine a new light on the possible application of Sentinel-2 data in this field.

Methods to estimate built-up areas have been experimented with since the dawn of remote sensing. As humanity entrenched itself further and further in the natural landscape, built up areas have become very prominent and are

therefore included in most land cover classifications. One of the most common methods for creating a land cover map is the supervised classification. In this method the classifier is "trained" by the selection of several training polygons within the image, the training polygons are areas where the land cover is known. Using the value of the different bands of each cell within the training polygon, the image is classified, pixel by pixel, using a maximum likelihood method. A study by Chen et al. (2004) shows how supervised classification methods perform better at relatively lower resolutions, with the best results yielded with a resolution between 20 m and 24 m. Another common method for the extraction of built-up areas is the use of indicators. Indicators, often normalized indicators (ND's), are based on the assumption that different land cover classes reflect different wavelengths of the light spectrum. This can be expressed as difference between different bands of the multispectral picture. While mostly used in vegetation studies, some of these indexes have been effectively used in the estimation of built up areas. The Normalized Difference Built-up Indicator (NDBI), has been successfully applied both in urban areas (Zha et al. 2003), and low density suburban areas (Vigneshwaran and Vasantha Kumar 2018). The use of more complex indicators, such as the Index-based Built-up Indicator (IBI) can also lead to better results as it takes into account vegetation and water bodies (Xu 2008; Varshney and Rajesh 2014).

1.2 AIM

This study tried to evaluate the suitability of different methods for extracting the built-up area of a refugee camp using Sentinel-2 data. Subsequently, these methods were applied in a time series analysis of the camp built up area to be used as proxy for the population. The methods compared in this paper were: Digitization, used in a previous study (Wendt et al. 2017); Supervised classification; and an Index Based Method based upon the use of IBI (Indicator-based Built-up Index). The suitability was evaluated by performing an accuracy assessment. Digitized high-resolution images were used as ground truth (Chen et al. 2004). The focus of the study was on finding methodologies that are cost effective and easy to implement.

2 METHODOLOGY

2.1 Software

The study was conducted using ArcGIS for the spatial analysis; the possibility of using QGIS was also evaluated, with the used tools having an equivalent in the open source program as well. The atmospheric correction of the data required the use of another spatial analysis software, SNAP, freely available on the ESA website. Furthermore, Google Earth Pro was also used extensively.

2.2 Study Areas

The chosen study areas were selected mostly on the basis of their growth since the introduction of Sentinel 2, in 2015. Camps in areas affected by recent humanitarian crisis, such as the Rohingya refugee crisis, were selected as more likely to show significant built-up area growth. Also taken into account, is the notoriety of the camp since information from more renown camp is easier to obtain. Furthermore, camps were enough cloud-free images to perform the time series analysis were available, were selected. After carefully screening a few possibilities, two camps were selected, Nyarugusu refugee camp, in Tanzania, and Kutupalong refugee camp, in Bangladesh.

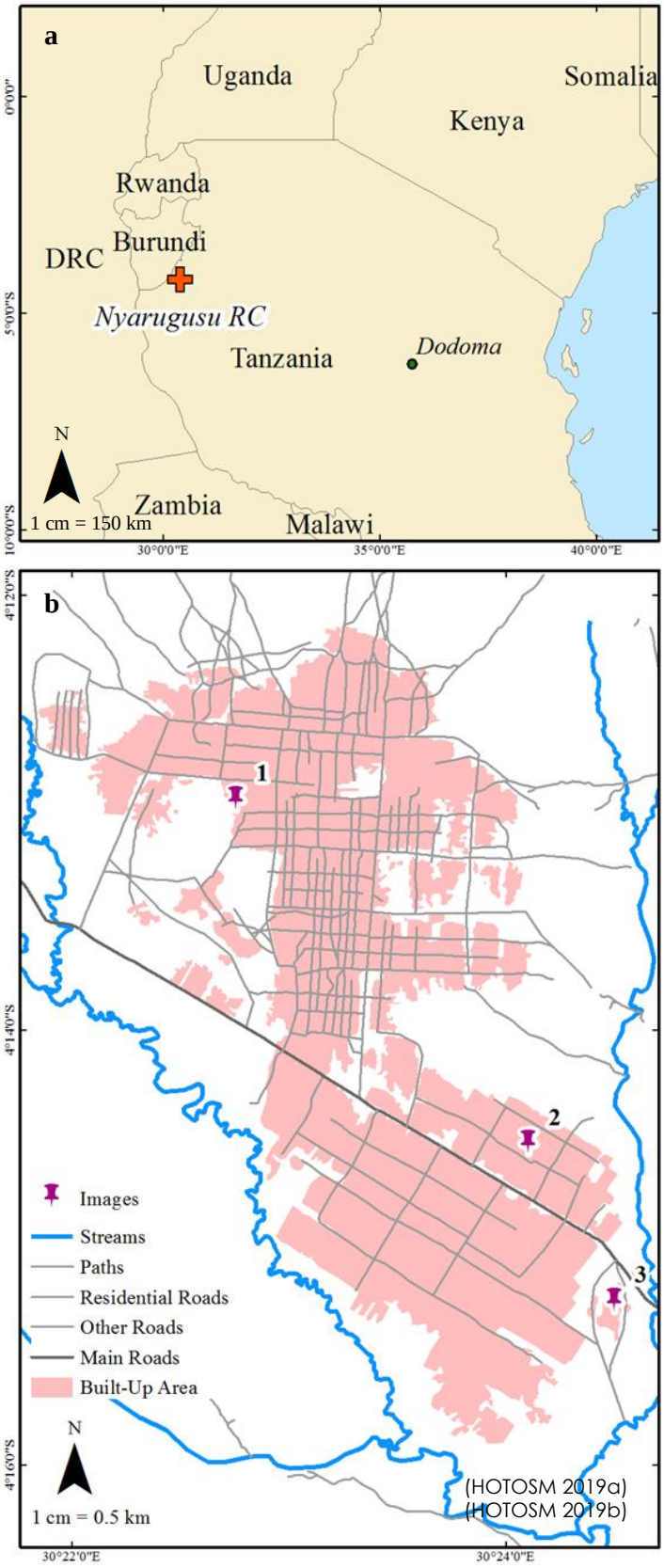
2.2.1 Nyarugusu refugee camp

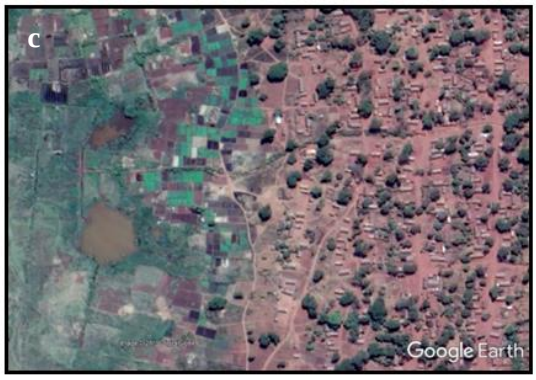
With a population of about 150.000, Nyarugusu is Tanzania's biggest refugee camp (UNHCR 2015b). It is located in the western part of the country (figure 1.a), in the province of Kigoma, east of Lake Tanganyika (Mweneake 2013). The camp was established by UNHCR and the Tanzanian government in the 90's to host Congolese refugees escaping from a civil war in the DRC. However, since 2015 the camp has seen a new influx of refugees, escaping from unrests in Burundi (UNHCR 2016b). An initial 110.000 Burundian were hosted in the camp until the government allowed them to resettle to other camps; approximately 65.000 Burundian refugees remained at Nyarugusu.

Tanzania's tropical climate is characterized by the migration of the Intertropical Convergence Zone (ITCZ), giving rise to two rain seasons: the "Vuli", from October to December, and the longer "Masika" from March to May (Wikipedia 2019b). The selection of satellite image had to be done taking into account of the seasons, to avoid overcast images.

By observing the area on Google Earth (figure 1), it can be noticed how the camp is located in a lush area, mostly surrounded by farmlands and with streams running along its southern and eastern borders. A small body of water is also located around the center of the camp. To the east, south and west, the camp is surrounded by farmlands (figure 1.c), whilst the area to the north is a dry grassland showing signs of grass burnings. The camp is vaguely L shaped, with the upper section comprised of the older, more established part, dating back to the '90s, here the houses are mostly traditional dirt huts and are sided by trees. On the other hand, the lower section is characterized by white and light blue tents in a regular pattern, constructed with the humanitarian aids (figure 1.d). Along the main road on the southern end of the camp is located a common market (figure 1.e).

Nyarugusu Refugee Camp – July 2017





1. Farms surrounding the camp
The Norther section of the camp dates back to the early '90s. The camp is surrounded by farmlands.
Image from Google Earth, May 2019

2. New section.
The southern section was established after 2015. It is mostly constituted of tents donated from the relief effort.
Image from Google Earth, May 2019

3. Common market.
On the southeastern end of the camp, there is a market, along the road, there is a market.
Image from Google Earth, May 2019

Figure 1: Nyarugusu Refugee Camp. Figure 1.a shows the position of Nyarugusu RC within the country of Tanzania. Figure 1.b shows the layout of the camp. Figures 1.c, 1.d and 1.e correspond to the point "images" 1, 2 and 3 from figure 1.b. Maps by the Author

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2.2.2 Kutupalong refugee camp

The camp of Kutupalong, also known as Kutupalong-Balhukali, is located in Cox's Bazar, in southeastern Bangladesh, close to the border with Myanmar (figure 2.a). The camp was established in 1991 but has grown in recent years as Rohingya refugees fled from ethnic and religious persecution in Myanmar. As of 2019, Kutupalong is regarded as one of the world's largest refugee camps. In the span of about two years, from 2016 to 2018, the population grew from around 34 000 to over half a million (UNHCR 2019a). Nowadays, the camp is not organized in a single unit, but it is constituted by several tens of camps organized in one giant camp, in the northeast of the region, with some smaller satellite camps to the south of it. In this paper we will consider part of the Kutupalong Refugee Camp the two major parts, composed by Kutupalong RC, and Camps: 1E;1W; 2E; 2W; 3; 4; 4 Ext; 5; 6; 7; 8E; 8W; 9; 10; 11; 12; 13; 14; 15; 16; 17; 18; 18; 20; and 20 ext.

Southeastern Bangladesh is characterized by a tropical monsoon climate with three main seasons: a warm and dry "winter" from December to February; a hot and humid "summer" from March to June; and a hot monsoon season from June to November (Wikipedia 2019a).

The camp is located in a lush forested area. A web of streams cuts through the hilly landscape; the dwellings are mostly located on top of the watersheds, while the areas closer to the streams are mostly farmed. Except from the original 1991 structure in the northeast, the camp is mostly unplanned and spawned rather organically following the natural landscape of the area. Nevertheless, the dwellings are well spread out and a network of roads can be observed branching from the main road to the east (figure 2.b). By observing time series images on Google Earth, we can see how the camp started as a small, organized settlement along the road, in the northeastern part. After 2015, the camp has started developing rapidly, mostly spreading over previously forested areas, and expanding in the southwest direction. Nowadays, the camp stretches for several kilometers and the two biggest sections have grown so big that only a couple hundred meters of farmlands remain between them (figure 2.e). The camp borders to the west to a major road and a river and has its own train station on the north eastern end (figure 1.c). Along the river and to the south we can observe the largest farmlands; while closer to the camp, the farms are smaller. To the west, we can see the remains of the forest that the cam replaced with its expansion, as well as small-scale farming and plots of lands used for other purposes by the inhabitants of the camp (figure 1.d).

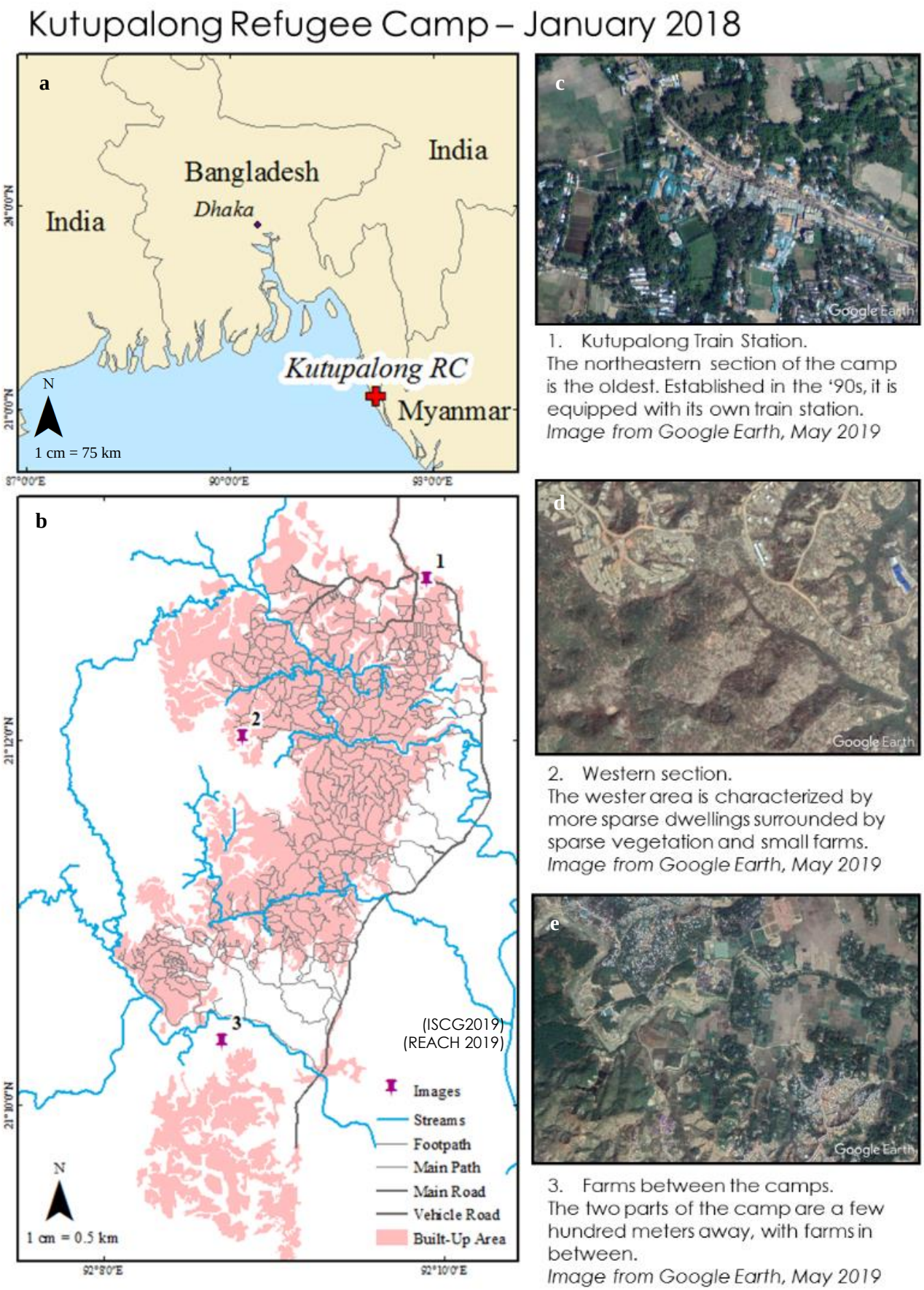

Figure 2: Kutupalong Refugee Camp. Figure 2.a shows the position of Kutupalong RC within the country of Bangladesh. Figure 2.b shows the layout of the camp. Figures 2.c, 2.d and 2.e correspond to the point "images" 1, 2 and 3 from figure 2.b. Maps by the Author

2.3 Landcover Classes

The landcover was classified into two classes, namely: Built-up, and Non-built-up. The Built-up area was defined as the dwellings and the paths and roads between them, but not the larger open spaces between the various blocks (Wendt et al. 2017). Buildings separated by single trees or small gardens were considered part of the built-up area, while areas of vegetation several trees deep, even if in between two blocks of buildings, were not considered built-up area.

2.4 Data

2.4.1 Sentinel 2 Data

The data was downloaded from Copernicus SciHub using its browser. Sentinel-2 data is open source and systematically uploaded onto the Browser. Sentinel-2's fleet is comprised of 2 identical satellites (Sentinel-2A and Sentinel-2B) guaranteeing global coverage of all land surfaces and coastal waters from 56° S to 84° N with a revisit time of 5 days. The satellite is equipped with a sensor capable to acquire optical imagery with 290 km wide swaths, with 13 bands ranging from 443 nm to 2190 nm, and a resolutions of 10 m, 20 m, and 60 m, depending on the band (See Table A1 in the appendix) (esa 2019b).

2.4.2 Atmospheric Correction

Sentinel 2 data is processed to correct for the sensor's geometry, this type of data is called Top-Of-Atmosphere and is referred to as L1C and is what can be downloaded from the ESA portal. Nevertheless, in order to use the data in calculations involving the value of the signal at the various wavelengths atmospheric correction and ground geometry have to be taken into account. This type of radiometrically corrected data is called Bottom-Of-Atmosphere, or L2A (esa 2019a). Starting from December 2018, L2A data is also available for direct download.

The correction from L1C to L2A was performed using the GIS Software SNAP using Sen2Cor(step 2019). Sen2Cor is a processor performing atmospheric, geometric, and cirrus correction to create Bottom-Of-Atmosphere from Top-Of-Atmosphere, as well as some ancillary data, in a JPEG2000 format. The plug-in Sen2Cor was downloaded and installed onto SNAP. The L1C data was then processed and used for some of the analysis.

2.4.3 Removal of Clouds

Cloud removal was performed by digitizing the clouds and their shadows and then assigned to the land cover classes using the nearest neighbor method. This was done in case the image was over-casted by tiny clouds (covering not more than 1-2% of the image) and no alternative image could be obtained.

2.5 Proposed METHODS

A flowchart depicting the three methodologies can be seen in figure 3.

2.5.1 Methodology 1: Index Based Method

The Index-based Built-up Index (IBI) was selected as Built-up area index for this study. The IBI is regarded as one of the most effective built-up indexes as it takes into account parameters for vegetation, water, built-up areas, and soil (Varshney and Rajesh 2014). It is calculated using an ensemble of NDBI (Normalized Difference Built-up Area Indicator), MNDWI (Modified Normalized Difference Water Index) and NDVI (Normalized Difference Vegetation Index). The value of NDBI is enhanced by subtracting the MNDWI and the NDVI. The values of the indexes were calculated for each cell using the value of the cell of the corresponding band of the Sentinel-2 image (Table A1 in the appendix). The various indexes IBI were calculated using the equations 1 to 5:

(Eq. 1)

$$NDBI = \frac{MIR - RED}{MIR + NIR}$$

(Eq. 2)

$$MNDWI = \frac{GREEN - MIR}{GREEN + MIR}$$

(Eq. 3)

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

(Eq. 4)

$$IBI = \frac{NDBI - \frac{MNDWI + NDVI}{2}}{NDBI + \frac{MNDWI + NDVI}{2}}$$

Therefore, the IBI itself can be directly calculated using this formula:

(Eq. 5)

$$IBI = \frac{2\mathrm{MIR} / (\mathrm{MIR} - \mathrm{NIR}) - (\mathrm{NIR} / (\mathrm{NIR} + \mathrm{RED}) + \mathrm{GREEN} / (\mathrm{GREEN} + \mathrm{MIR}))}{2\mathrm{MIR} / (\mathrm{MIR} - \mathrm{NIR}) - (\mathrm{NIR} / (\mathrm{NIR} + \mathrm{RED}) + \mathrm{GREEN} / (\mathrm{GREEN} + \mathrm{MIR}))}$$

In order to operate with Indexes Bottom-Of- Atmosphere data is recommended as the methods relies heavily on calculations using the values of the signal at the different bands. Therefore, the data was firstly transformed from L~~2~~1C to L2A, if the latter was not already available. Subsequently, the three visible bands (2, 3, and 4), plus the Near Infra-Red (NIR) (8), and the Near Infra-Red (NIR) (11) were selected and used to calculate the IBI. The IBI was then reclassified using threshold values selected manually in order to obtain the best observable results (Xu et al. 2013), these results are compared to Google Earth, as well as ESRI Basemap. For coherence reasons, the same values of thresholds were selected for images taken during the same season but different years. Later, the image was submitted to majority filtering, to remove noise. Finally, all the individual areas with an area smaller than 2500 m^2 were removed as the built-up area is expected to be somewhat contiguous. 2500m2 corresponds to a 5 by 5 pixel square.

2.5.2 Methodology 2: Supervised Classification Method.

As for the previous methodology, the working data should consist of Bottom-Of-Atmosphere data. Therefore, the data were firstly transformed from L1C to L2A, if not already in the latter format. Subsequently, the three visible bands (2, 3, and 4), the NIR (8), and the two SWIR (11 and 12), were selected and combined into a single multiband file. These six bands were selected as they are commonly used for estimation of land cover. Training polygons were then created over areas where the land cover could be easily identified. Due to the heterogeneity of the camp, different types of landcover classes had to be created for each of the two main land cover classes. A maximum likelihood method was then performed to create the land cover for the whole study area. After these first results, the training polygons were tweaked and adjusted and the classification re performed; this was then repeated until a good result was achieved. The land cover was then reclassified into the two main classes and submitted to majority filtering and removal of all the areas smaller than 2500 m^2.

2.5.3 Methodology 3: Digitization Method.

Since this approach does not require any calculation using the different bands, but is solely based on the user's observation, it could be performed directly onto the Top-of-Atmosphere data. Firstly, the three visible bands (2, 3,and 4), the NIR (8), and the two SWIR (11 and 12), were selected and combined into three multiband files: real color composition, using the three visible bands; False Color Composition (FCC) using 2, 3 and 4; and finally, False Color Composition Urban (FCCU) using 4, 8 and 11, the latter displaying bare soil and urban in a reddish tint. The digitization was performed by creating a polygon feature and editing it. The three compositions were used alternatively to try and understand the land cover composition. High resolution images from Google Earth, as well as ESRI Basemap, were also used, bearing in mind that they might be years apart. To avoid bias, the high-resolution Images later used as ground truth were not used in this process.

2.6 Accuracy Assessment Method

In order to evaluate the accuracy of the three methods, high resolution imagery was chosen as ground truth and used to generate the reference built-up area. The high-resolution imagery selected was either the ESRI Basemap or Google Earth imagery. Firstly, the reference images were carefully digitized. In order for the accuracy assessment to be as precise as possible, it was conducted only on those cloud free images that were as close as possible to the date that the high-resolution image was taken. A confusion matrix of the two classes was generated, for each methodology, for both study areas. Finally, accuracy and kappa values were calculated using the equations (6) and (7). The value of accuracy indicates overall the effectiveness of the classifier, while the kappa coefficient considers of how effective the classifier is compared to chance alone.

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Number\ of\ Values} \quad \text{(Eq. 6)}$$

$$Kappa = \frac{N \sum_{i=1}^{n} mi,i - \sum_{i=1}^{n}(Gi\ Ci)}{N^2 - \sum_{i=1}^{n}(Gi\ Ci)} \quad \text{(Eq. 7)}$$

Where:

- i - is the class number
- N - is the total number correctly classified
- $m_{i,i}$ - Correctly classified in class i
- C_i – number values belonging to class i predicted by the classifier
- G_i – number of values effectively belonging to class i.

2.7 Time Series

The three methodologies were used to create a time series of the Built-up area of the two camps. Each approach was repeated on each of the images selected for the series. While for the Index Based Method the method had to be repeated completely at each iteration of the time series, the Supervised Classification Method was performed re using the same training polygons of the previous step and editing them to fit the new land cover, while the Digitizing Method was performed by directly editing the previous step polygons.

2.7.1 Population Data

Population data was obtained from different sources for the two camps (See table A2 in the appendix). The data for Nyarugusu was obtained from the camp prospects released by UNHCR. In the case of Kutupalong, the data was inconsistent and had to undergo further adjustments. The refugee population of the whole district was obtained for the whole time series (Corliss et al. 2019) while that of the area considered camp was obtained only on one date (UNHCR 2019a). The population of the camp for the whole time series was therefore calculated by considering the fraction of refugees inhabiting the camp to be constant.

2.7.2 Correlation

The population data was then correlated to the built-up area. The statistical significance of the correlation was then estimated through a p-test, with significance of 0.05.

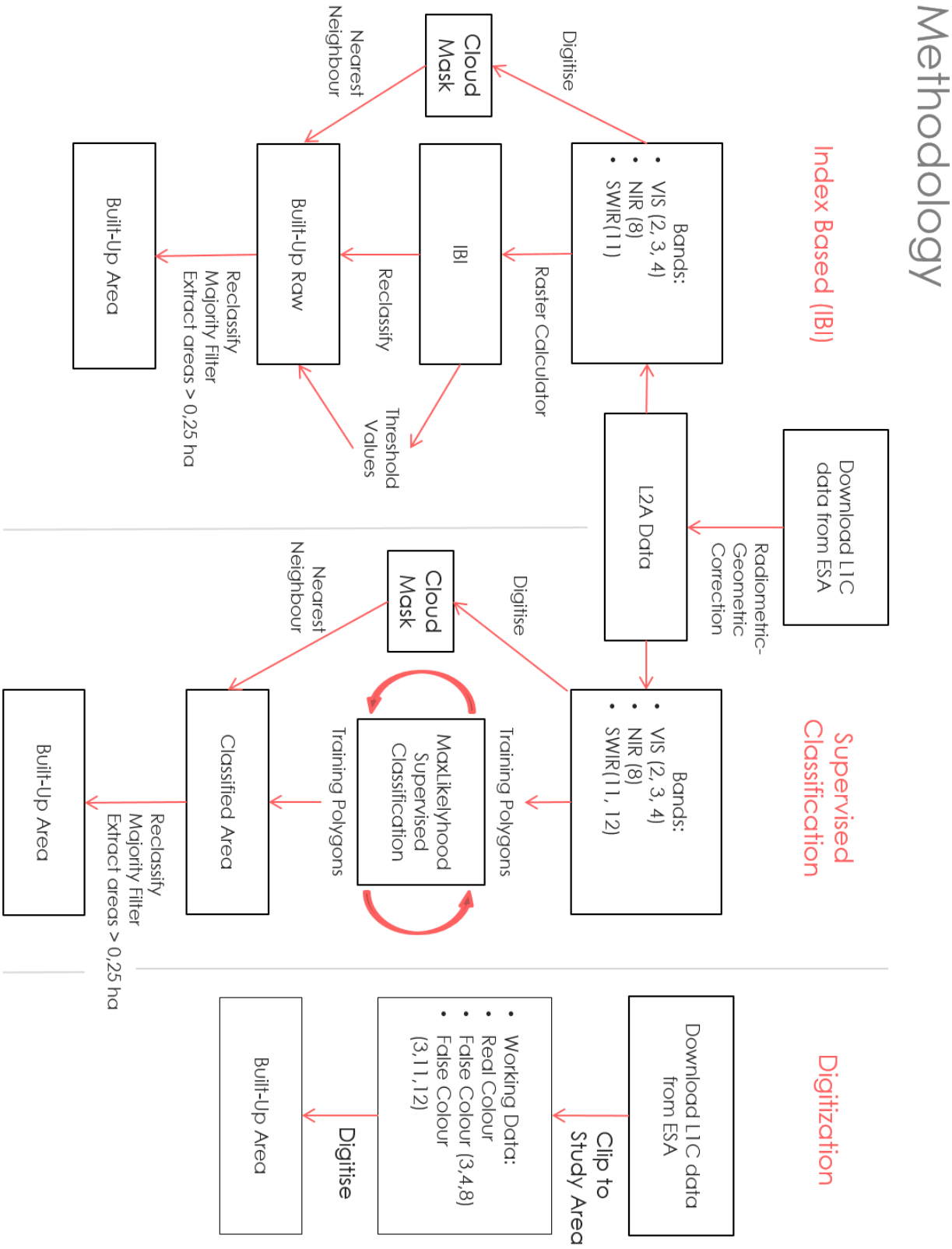

Figure 3: Flowchart of the Methodologies

3 RESULTS

3.1 Built Up Area Comparison

The three methods presented in this paper were applied on the same Sentinel-2 imagery in order to compare their efficacy in determining the built-up area. For the camp of Nyarugusu, the selected imagery was collected on June the 27th 2017, this was chosen so that it could be compared to the high-resolution imagery available through ESRI Basemap (World View-3), captured on July the 13th of the same year. In the case of Kutupalong, the Sentinel-2 images were collected on December the 15th 2017 and validated using imagery from Google Earth Pro (DigitalGlobe 2019)from January the 17th 2018. The built-up area is assumed to be unchanged between the reference image and the working one. Since both reference images were collected later than the Sentinel-2 ones, the reference image is expected to overestimate slightly the built-up area.

Of the three methods, the Index Based Method yielded larger areas in both study areas. In the case of Kutupalong, the Index Based Method has estimated an area twice that obtained with the Supervised Classification Method and three times that obtained with the Digitization Method (Figure 4). In the case of Nyarugusu this is not as pronounced but still observable. The Supervised Method yielded the second largest area in the case of Nyarugusu, but the third in the case of Nyarugusu.

3.2 Reference area

The built-up area obtained from the reference imagery was digitized. The total area of the two camps turned out to be roughly the same, about 1232 ha for Nyarugusu and 1132 ha for Kutupalong. In the case of Nyarugusu the closest estimation of the area was that obtained with the Digitization method, while for Kutupalong the closest was obtained via Supervised Classification.

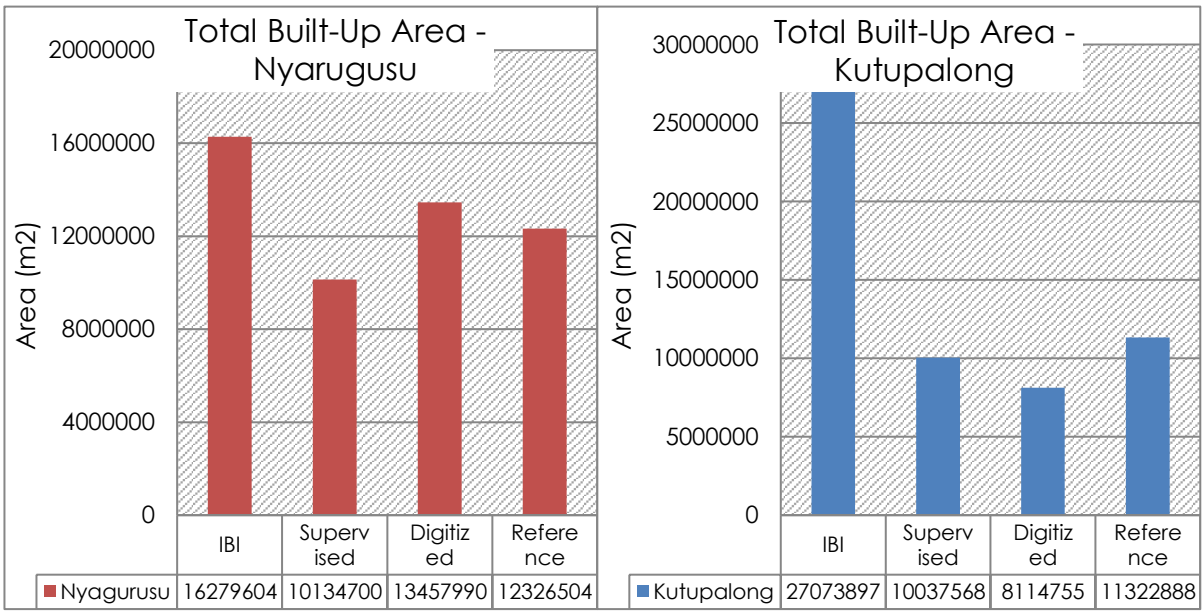

Figure 4: Built-up area Comparison

3.3 Accuracy Assessment Comparison

The areas wrongly classified as Built-Up (false positives) were labeled as Type I Error, while the opposite (false negatives) as Type II Errors. As we can see in Figure 5, whist the Index Bases Method largely identified the biggest areas; a good part of it was actually non-built-up area. In both cases in general, but in Kutupalong in particular, this was so prominent that the Type I Error is larger than the correctly identified Built-up area. On the other hand, both the Supervised Classification Method and Digitization Method have larger Type II Error than Type I Error, meaning that some parts of the refugee camp were not correctly identified and were labeled as Non-Built-up areas instead.

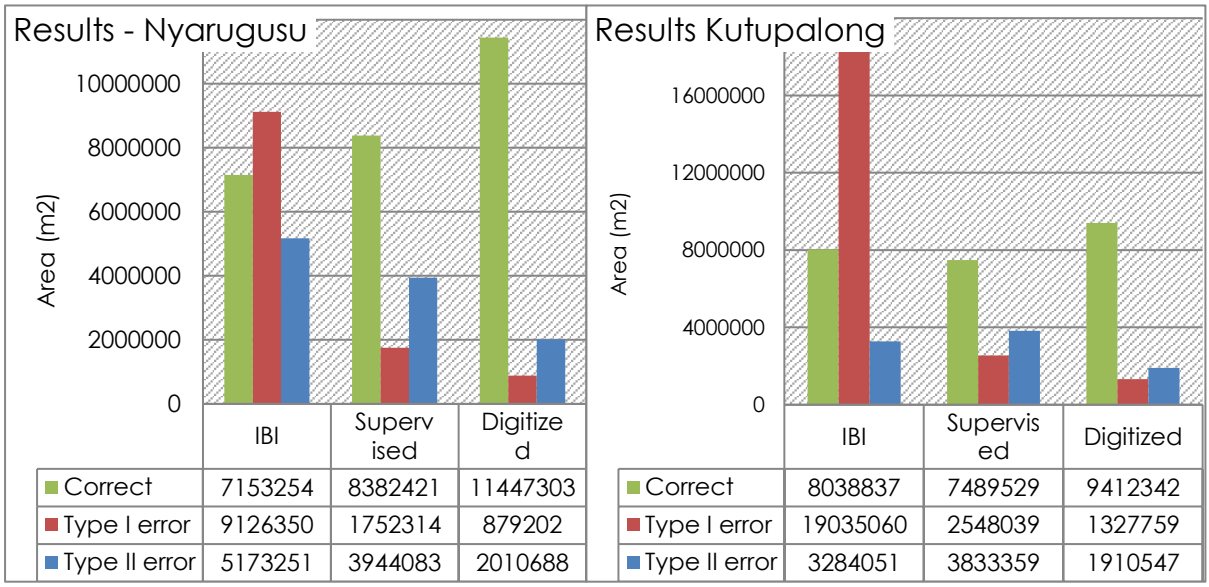

Figure 5: Results from the Confusion Matrix

Both accuracy and kappa are quite consistent amid the different methods and between the two study areas (Figure 6). While the calculation of the accuracy reveals that all three methods are relatively good at finding Built-up area, all the cases but one having an accuracy higher than 0.8, the kappa values reveal how some of the methods do not perform much better than chance alone (chance alone corresponding to a kappa of 0). In particular, the Index Based Method has a relatively low kappa, despite of the decent accuracy. This is due to the very large false positives that it generated. The second-best performing method is the Supervised Classification Method; this is true for both the accuracy and the kappa. In both study areas, the best performing method, turned out to be the Digitization Method (kappa= 0.84; 0.85).

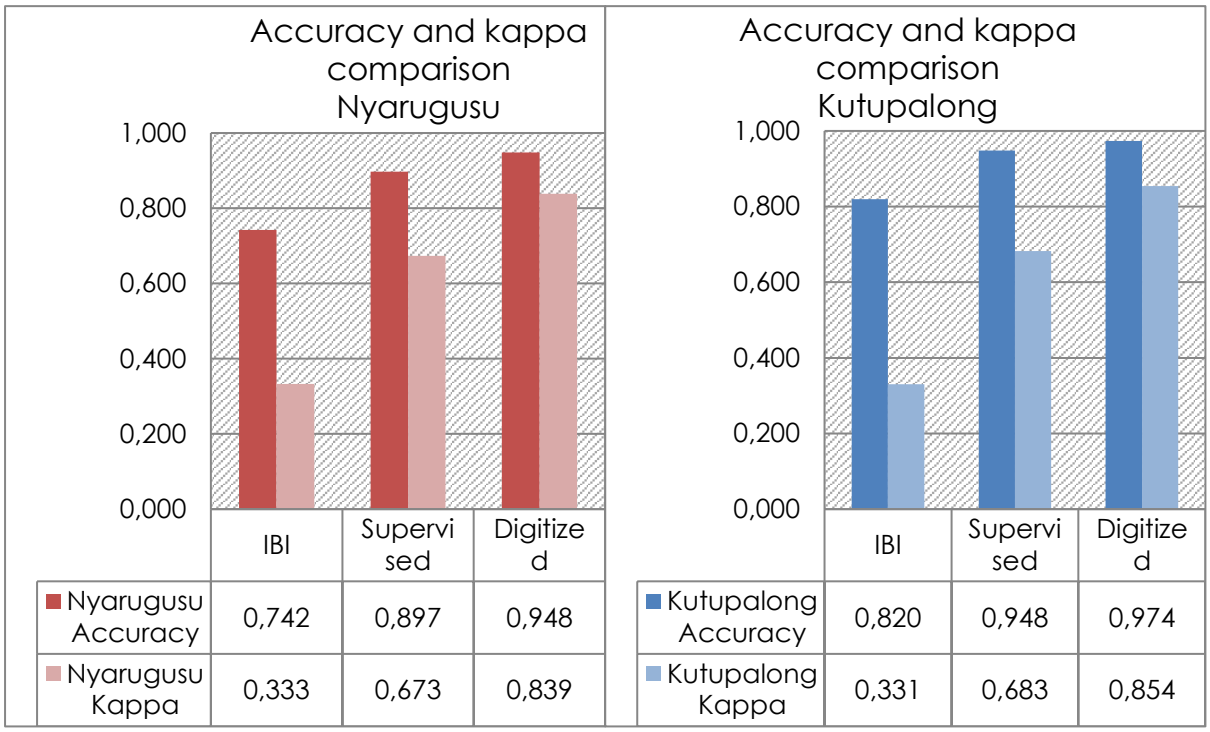

Figure 6: Accuracy and Kappa Comparison

3.3.1Classification Errors

3.3.1.1 Classification Errors in Nyarugusu Study Area

In the case of Nyarugusu, most of the Type I Error was concentrated in the area north of the camp (Figure 7); this is especially true for the Index Based Method. In the reference image we can see how this area was overall drier and characterized by sparse vegetation. Another source of Type I Error was found in the south east, here the presence of the main entry road and that of a large bare area used as marketplace have led to errors. The Supervised Classification Method shows more evenly distributed and very limited false positive, with several small specks sprinkled around the camp. The Digitization Method shows some areas of Type I Error around the edges of the camp, mostly in areas where the lower resolution of Sentinel-2 did not allow for the same level of detail as from the reference image.

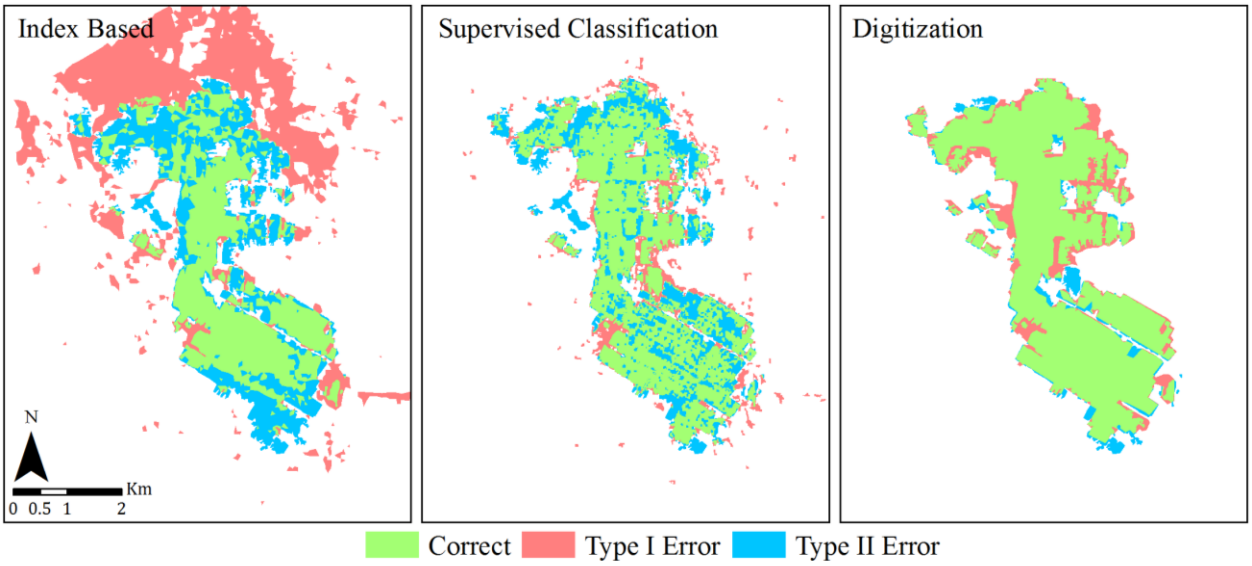

Figure 7: Errors in the Nyarugusu Study Area

Type II Error of the Index Based Method are mostly concentrated in the very south, and in the northwest. In the south, the most recently constructed area of the camp is located, while in the north we have the oldest part; in this area, trees and hedges surround the dwelling, affecting their spectral signature. The northern area is also where the false negative in the Supervised Classification Method are located. The same can be seen in the small section detached from the main camp to the west, which has been completely missed out by this method. The main source of Type II Error in the Digitization Method is the area roughly in the center of the camp, where a large section of camp was missed out during the digitization. This area is characterized by sparse dwellings surrounded by relatively dense vegetation. This area was only correctly classified by the Supervised Classification Method.

3.3.1.2Classification Errors in Kutupalong Study Area

In the Index Based Method, two main sources of Type I Error can be observed: to the west a large feature is flanking the camp, while to the southeast lays a large branching object. By examining these areas in the reference image, it can be observed that the first area is composed of small plots of land poorly farmed and used for other generic purposes by the inhabitants of the camp and are generally devoid of vegetation. The second area is a large and flat riverbank. Whilst the river was correctly classified, most of the farmlands surrounding it have been classified as Built-Up; likely, these farms are bare during this season. In the Supervised Classification Method, false positive is limited to very few dots. In the Digitization Method, the main source of this error is the stream features running through the camp. While at higher resolution these features could easily be identified, at the resolution of Sentinel-2 this was impossible.

Type II Error is mainly located in two areas: To the north and northeast, this can be seen in the first two methods; and in the northwest, this is true for the Supervised Classification Method and the Digitization Method. The first area is the oldest part of the camp, originating from the 90's. This is constituted of well-

established dwellings, with tin roofs and with some vegetation in between the buildings, likely trees and hedges from people's gardens. The second area is a newly established section of the camp. For unclear reasons, here the dwellings are particularly further apart and are surrounded by small plots of farmland. The low density likely made this area hard to identify while digitizing or drawing the training polygons.

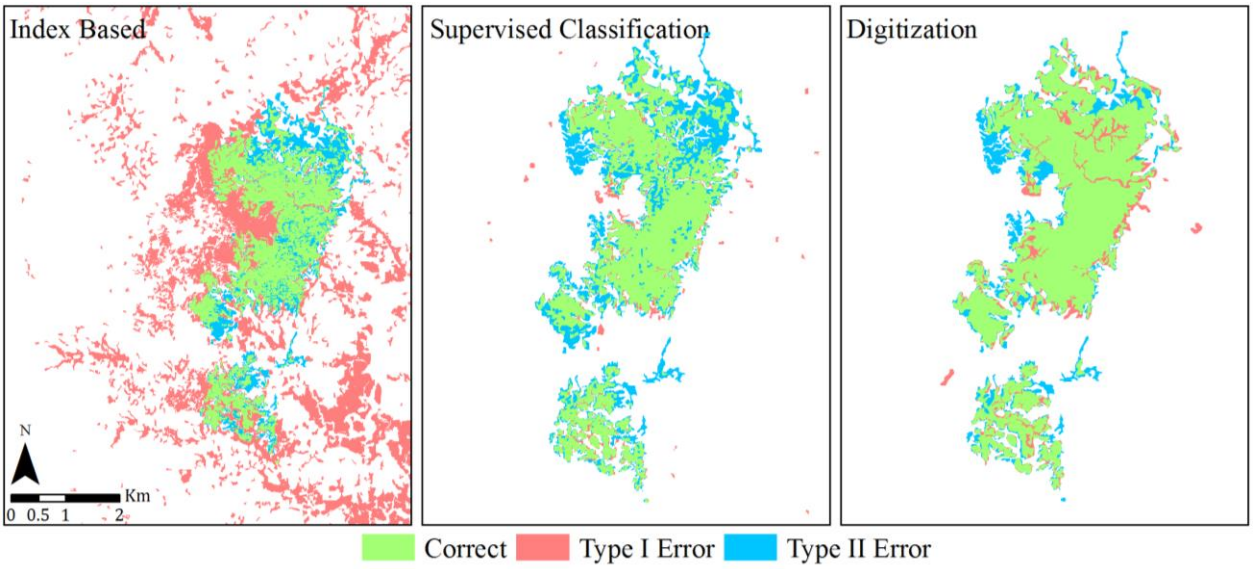

Figure 8: Errors in the Kutupalong Study Area

3.4 Time Series

The side-by-side comparisons of the classified images from the different time steps can be seen in figure 1 and figure A2 in the appendix.

3.4.1 Nyarugusu Refugee Camp

While clearly showing some differences, two of the three methods yielded similar results. The overall size of the Built-up area is comparable across the three methodologies and the general trend is slightly positive for all three approaches (Figure 9). By far the biggest issues can be seen in the Index Based Method. Over the short period of the time series analysis, the built -up are was expected to have a positive trend as both camps were selected for their increase in population during the years of the study. Even though the trend is positive, the overall area unrealistically shrinks and expands drastically over short periods of time. The Supervised Classification Method yielded satisfactory results, with the only slight outlier being the June 2016 point. The results from the Digitization are very satisfactory as they show a monotonous increase.

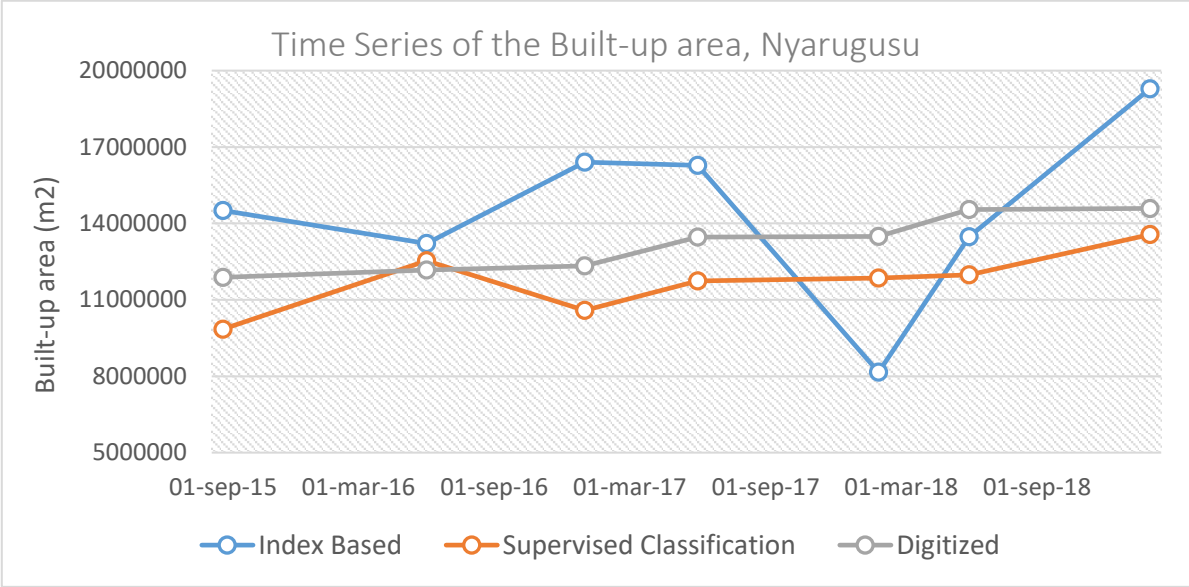

Figure 9: Nyarugusu Time Series of the Built-up area

In figure 10, we can observe the spatial development over time using the three different procedures. The Index Based Method does not show any coherency, as the sheer amount of errors outside of the main Built-up area adds up to a confusing result. On the other hand, results from the other two methods are strikingly similar, with the only difference being the presence of specks of error surrounding the results from the Supervised Classification Method. In both cases we can see the main areas of development. Firstly, to the very southern tip we can observe a protuberance being expanded over time. Secondly, in the central area to the right of the "hole" in the camp, we can see the built-up area growing and bridging-up the two sides, this can be better appreciated in the digitized image. Lastly, we can observe the creation and development of a section of camp to the west, detached from the main body, starting around 2017; the Digitization Method represents this better.

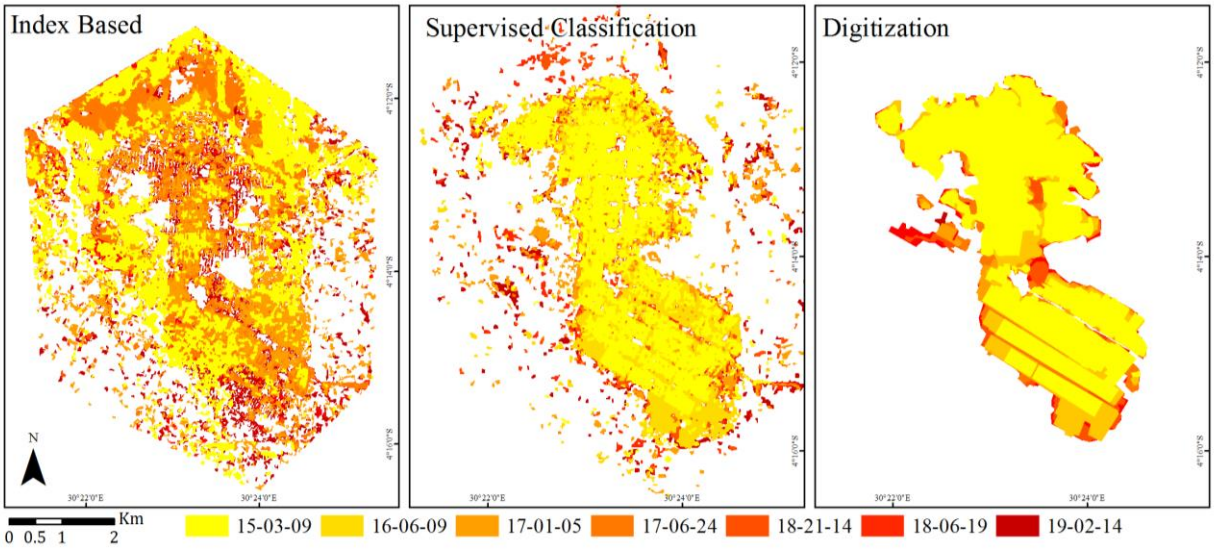

Figure 10: Nyarugusu Time Series (The hexagonal shape is the result of the working extent used).

3.4.2 Kutupalong Refugee Camp

Unlike the case of the other study area, the time series created with Index Based Method differs greatly from that obtained from the other two (Figure 11). Once again, the overall trend is positive in all cases but, in the case of the Index Based Method the variation between each point is extremely erratic. In contrast, the other two methods show very good agreement. The biggest difference between the two methods is the rate of growth. While the Supervised Classification Method shows a smoother growth, this is particularly true if we consider November 2017 an outlier, the Digitization method has a more sudden increase February and December 2017.

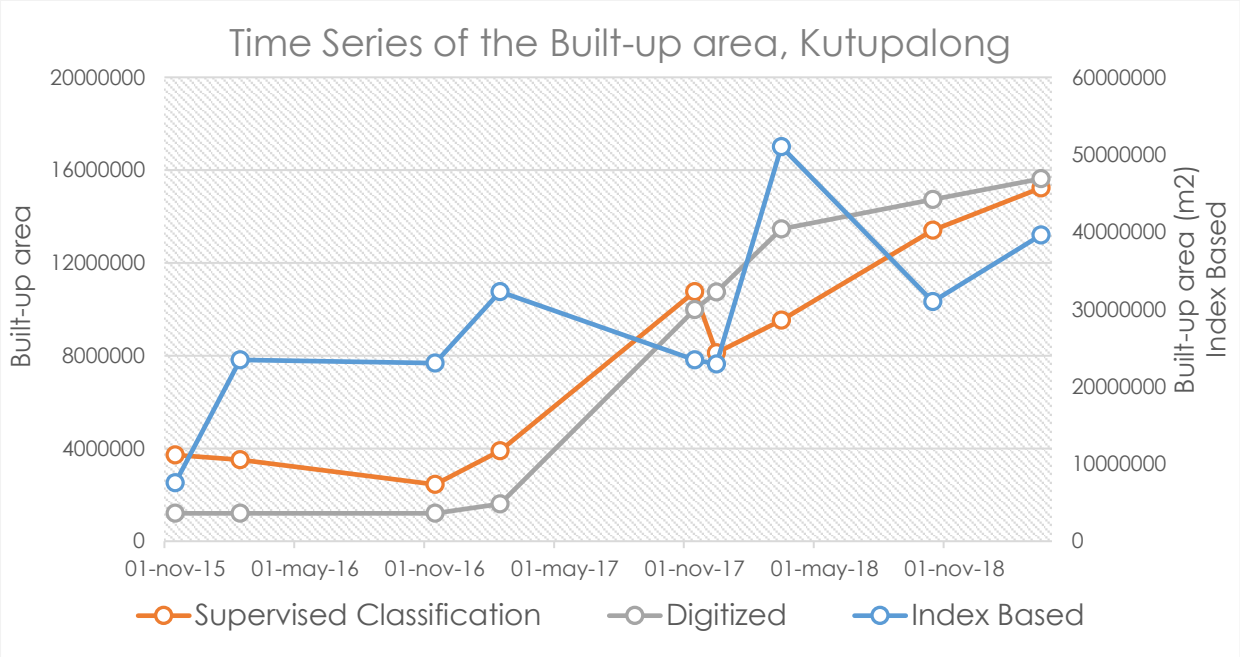

Figure 11: Kutupalong Time Series of the Built-up area

The spatial comparison of the three approaches can be seen in figure 12. Even more than in the first case, the results from the Index Based Method are dotted in areas of error and hard to interpret. By contrast, the other two methods yielded remarkably similar results. In both cases we can see how the initial camp was just a fraction of what it becomes, entirely concentrated in the northeastern part. The first two points are not shown in figure 10, as they are virtually identical to the third one. The growth took place from this older sector in a southwest bound direction. The biggest single step growth is that between February and November 2017.

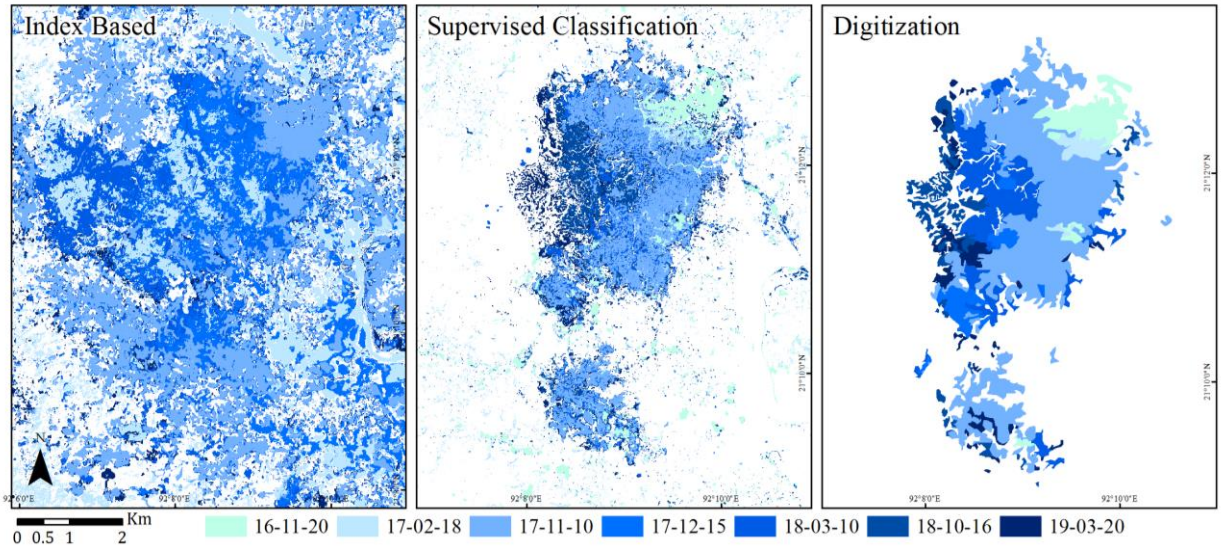

Figure 12: Kutupalong Time Series

3.5 Population

3.5.1 Nyarugusu

Following the unrests in Burundi in August 2015 a large number of refugees sought shelter in the camp and, at the time that the first point of the time series is collected, the estimated population overreached 170000 (Figure A3 in the appendix). Later the same year the Tanzanian government provided for the refugees to be redistributed over other camps (UNHCR 2016b), allowing the population to settle around 130000. From then on, the population has steadily grown, with a faster growth between July and November 2017, likely caused by further deterioration in the political situation in the first half of the same year (Amnesty International 2018)

3.5.2 Kutupalong

The population of Kutupalong camp grew from an estimated 50000, at the beginning of the time series in November 2015, to over 700000 by April 2019 (Figure A4 in the appendix). Nevertheless, the increase is not linear but takes place almost entirely in the span of few months, between July and December 2017, following a series of violent events around the same period, particularly a brutal military-led suppression in August 2017 (The Guardian 2019).

3.6 Correlation between Built-up area and Population.

A linear correlation was carried out between the Built-up area of the time series of the two study areas obtained using the three methodologies, and the population of the two camps; six correlations were obtained in this way. The amount of points used for each correlation is too low to draw any definitive conclusion (7 for Nyarugusu and 9 for Kutupalong), nevertheless this should be still considered of some significance. In the case of Nyarugusu, the first point of

the time series was excluded as the abnormal amount of people residing in the camp at the moment was not permanent; the point considered an outlier. The results from the correlations are displayed in table 1. In the case of Nyarugusu no correlation was found with the area obtained with the Index Based Method. In the case of Kutupalong a weak correlation can be detected (r2 = 0.407); nevertheless, this is significant. The Supervised Classification Method showed almost no correlation for the first study area (r2 = 0.246) but achieved a good correlation for the second study area (r2 = 8.16). Nevertheless, both correlations are found to be significant. Finally, the best performing methodology was the Digitization. Both cases showed very good correlation values and both correlation coefficient were found to be significant.

Table 1: Results from the Correlation

	NYARUGUSU			**KUTUPALONG**		
	IBI	*Supervised*	*Digitized*	*IBI*	*Supervised*	*Digitized*
r2 coefficient	0.003	0.246	0.828	0.469	0.816	0.949
Degrees of Freedom	5	5	5	7	7	7
Critical Values t	1.476	1.476	1.476	1.440	1.415	1.415
t value	0.126	1.560	6.783	2.988	7.697	16.019
Significance	No	Yes	Yes	Yes	Yes	Yes

4 DISCUSSION

4.1 Atmospheric Correction: A Problem Non-Problem

As this paper was meant to explore quick and easy to use methods, the need for atmospheric and geometric correction hinders on the methodologies that require it: Index Based Method and Supervised Classification Method. Transforming L1C data into L2A data is a lengthy and somewhat complicated process. Nonetheless, ESA has started releasing Bottom-of-Atmosphere data to download from their browsers starting from December 2018. This removes the issue and dramatically shortens the time necessary to perform either of the two methodologies that require the correction.

4.2 Methodologies: Strengths and weaknesses

As results show, the most accurate of the three methodologies is Digitization. Comparably, the other two approaches underperformed, or even, such as the case of the Index Bases Method, failed. Nevertheless, one must consider the different applications that the various approaches can satisfy. The use of Indexes, fails in estimating the area, as pointed out by its low kappa. The biggest shortcoming of the method was the overestimation of the Built-up area, as bushy areas and uncultivated farms are often erroneously labeled as such. Nevertheless, the Type II Error is somewhat in line with the other two methods, meaning that the method is not very likely to miss existing built-up areas. Since the method is very quick to implement, and its speed does not depend on the size of the area, one could consider its application in individuating settlements on a vast area. Still, better methods might be available for this task.

Second best method turned out to be the Supervised Classification. Even though this methodology gave satisfactory performances, it comes with its own limitations. The approach is very fiddly, as it might require several rounds of tweaking of the training polygons before obtaining satisfying results, and, still requires an experienced user, as it is still to know when the classified area best matches the reality. Nonetheless, this method gave good results and even outperformed the Digitization in some tasks. One example is the case of the section close to the center of the Nyarugusu Refugee Camp that was erroneously mislabeled by the other two methodologies. This area lies to the right of a spot of vegetation without dwellings and is composed of sparse dwellings surrounded by trees. It was classified erroneously as Non-Built-Up while digitizing as it was considered only vegetation. Nevertheless, the Supervised Classification managed to pick up some subtle differences and correctly labeled it as built-up. Another case are the streams crisscrossing the camp in the second study area. Due to their narrowness and irregular shape, these details were lost while digitizing, but were correctly recognized by the Supervised Classification Method. However, the accuracy of this method hinges on the ability of the operator to properly designing training polygons, making the method very dependent on the user's experience.

For the purposes of this paper, the best approach is the Digitization. Not only this methodology can work with L1C, greatly shortening the time required if the

L2A data was not readily available, but also ensures the best accuracy of the three approaches. Still, some data preparation is required, as the creation of False Color Compositions might require some time (even though these compositions can be downloaded together with the single bands from some browsers, such as EO Browser). Nonetheless, the other two methods can still find some applications in this field. Calculating the IBI of a large area might be a quick way of individuating settlements, if no better methods are available, while using Supervised Classification to generate Built-up areas could help the digitization to notice those smaller and irregular features that the untrained eye could otherwise miss out.

In all three cases, having high resolution imagery to consult is key for understanding the estimated Built-up area. For this purpose, the use of Google Earth or other similar services is essential. Even though the imagery might not be up to date, it usually displays images from sever years, making it possible to compare it to our estimation. Google Earth and Google Maps are great tools for exploring area with which one would otherwise be unfamiliar. For example, Google Maps has 360 photos taken with drones over Kutupalong Refugee Camp, and pictures of Nyarugusu Refugee Camp common market, allowing the operator to get the feeling of what one is looking at. Google Earth is generally more up to date than other services, such as the ESRI World Map.

Another source of geographic information is OpenStreetMaps. Over the years, the service has developed into a highly accurate world map, rivaling and often exceeding its rivals. This is particularly true in the case of developing countries, where other services, bound to commercial purposes, do not show interest. Even more so, the Humanitarian OpenStreetMaps Team (HOT) is a volunteer-based organization devoted to create maps of areas under humanitarian crisis. Many refugee camps around the world have been mapped by the volunteers and this data is freely available. This data is often used by humanitarian organization to organize relief operations (HOTOSM). The main issue with this data is the same that affects the Google Earth Imagery: it is rarely up to date, as volunteers work with open source data. Nevertheless, downloading and consulting this type of data can help understand the study area. One example, features such as roads and rivers used in the creation of figure 1 and figure 2 of this report were downloaded from the Humanitarian Data Exchange website (humdata.org) and were created during a Humanitarian Mapping campaign.

4.3 Time Series and Population

By far the methodology performing the best in the creation of a time series was the Digitization. One reason for this was the fact that this methodology does not depend on atmospherically corrected data to operate, this greatly shortens the operation time for this methodology. In addition to this, while the Index Based Method required a completely new attempt at extracting Built-up area at every step of the time series, Digitization allowed to take the feature created for the previous step and edit it to fit the changes in Built-up area. The other reason for this method superiority is the overall accuracy; digitizing came out on top as the most accurate approach for extracting Built-up area. This is

further confirmed by the correlation between the Built-up area and the population, seemingly confirming this method's effectiveness.

While Wendt (2017) already recognized the possibility use of the Built-up area as a proxy for the population in his paper, this study further supports them as the results from the correlations are striking. The fact that natural or human borders do not bind these camps, allows the camps to expand freely while keeping their density relatively constant all throughout. Nevertheless, this correlation suffers of two main issues. Firstly, the data used for the population had to undergo some adjustment, weakening the reliability of these findings. Secondly, the number of points used was too low to derive definitive conclusions and was limited by time constrain and availability of non-cloud casted pictures. Still, since population data was extrapolated and built-up area is unlikely to expand and shrink in the span of few months, it is likely that a correlation performed on the same study areas, but with denser points, would yield similar results.

4.4 Further Studies

The study leaves the door open to further studies, like:

- Repeating the study on different study areas, in different climatic regions.
- Conducting a more in-depth study only on the accuracy of the Digitation method with more study areas.
- Creating a Time-Series with more points in order to have a more significant correlation.
- Improving the Supervised Classification by including texture (Bramhe et al. 2018) or pairing it with segmentation methods (He et al. 2010).
- Expanding the time series further using Landsat, even though the lower resolution of the latter (30 m) might influence the result.

5 Conclusion

All in all, of the methodologies examined in this study, the most effective at extracting the Built-up area of a refugee camp from Sentinel-2 imagery, was the Digitization, as described in the Methodology section. Nevertheless, the other two approaches that we analyzed could still be used as a support to this methodology. In addition, external information, such as Google Earth or OpenStreetMaps data should be consulted in order to understand the area.

The results from the correlation between the Built-up area of the time series and the population support the use of the Built-up area as proxy for the population. This is likely because the refugee camps do not tend to densify, as they grow larger.

To conclude, the situation of refugee camps is utterly complex and humanitarian organizations have to do their best with the resources available. Over the last few years, more and more open source remote sensing data has become available, and its quality keeps increasing. We have just started exploring all the ways to use this data to ease the humanitarian efforts and, luckily for us, people's goodness is abundant and free.

Thank you all,
Riccardo

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6 Appendix

Table A1: Sentinel- 2A and Sentinel-2B bands. This table shows the details for both satellites in the Sentinel-2 fleet. For the purpose of this paper, the two satellites were considered to be identical.

Sentinel-2 bands	*Sentinel-2A*		*Sentinel-2B*		
	Central wavelength (nm)	*Bandwidth (nm)*	*Central wavelength (nm)*	*Bandwidth (nm)*	*Spatial resolution (m)*
Band 1 – Aerosol	443	21	4422	21	60
Band 2 – Blue	492	66	492	66	10
Band 3 – Green	560	36	559	36	10
Band 4 – Red	665	31	665	31	10
Band 5 – Red edge	704	15	704	16	20
Band 6 – Red edge	741	15	739	15	20
Band 7 – Red edge	783	20	780	20	20
Band 8 – NIR	833	106	833	106	10
Band 8A – Narrow NIR	865	21	864	22	20
Band 9 – Water vapor	945	20	943	21	60
Band 10 – Cirrus	1374	31	1377	30	60
Band 11 – MIR	1614	91	1610	94	20
Band 12 – SWIR	2202	175	2186	185	20

Table A2: Sources of Population Data. The data was created and distributed by UNHCR through different sources.

Nyarugusu		
Date	*Population*	*Source*
31 Jul 2018	*153024*	*(UNHCR 2018)*
31 Oct 2017	*149376*	*(UNHCR 2017e)*
30 Jun 2017	*136631*	*(UNHCR 2017b)*
31 May 2017	*136167*	*(UNHCR 2017d)*
31 Mar 2017	*134696*	*(UNHCR 2017c)*
16 Jun 2016	*130249*	*(UNHCR 2017a)*
11 Oct 2015	*167128*	*(UNHCR 2015a)*
Kutupalong		
From Jun 2017 To Dec 2018	*From 170000 to 909000*	*(Corliss et al. 2019)*
15 Apr 2019	*925736*	*(UNHCR 2019a)*

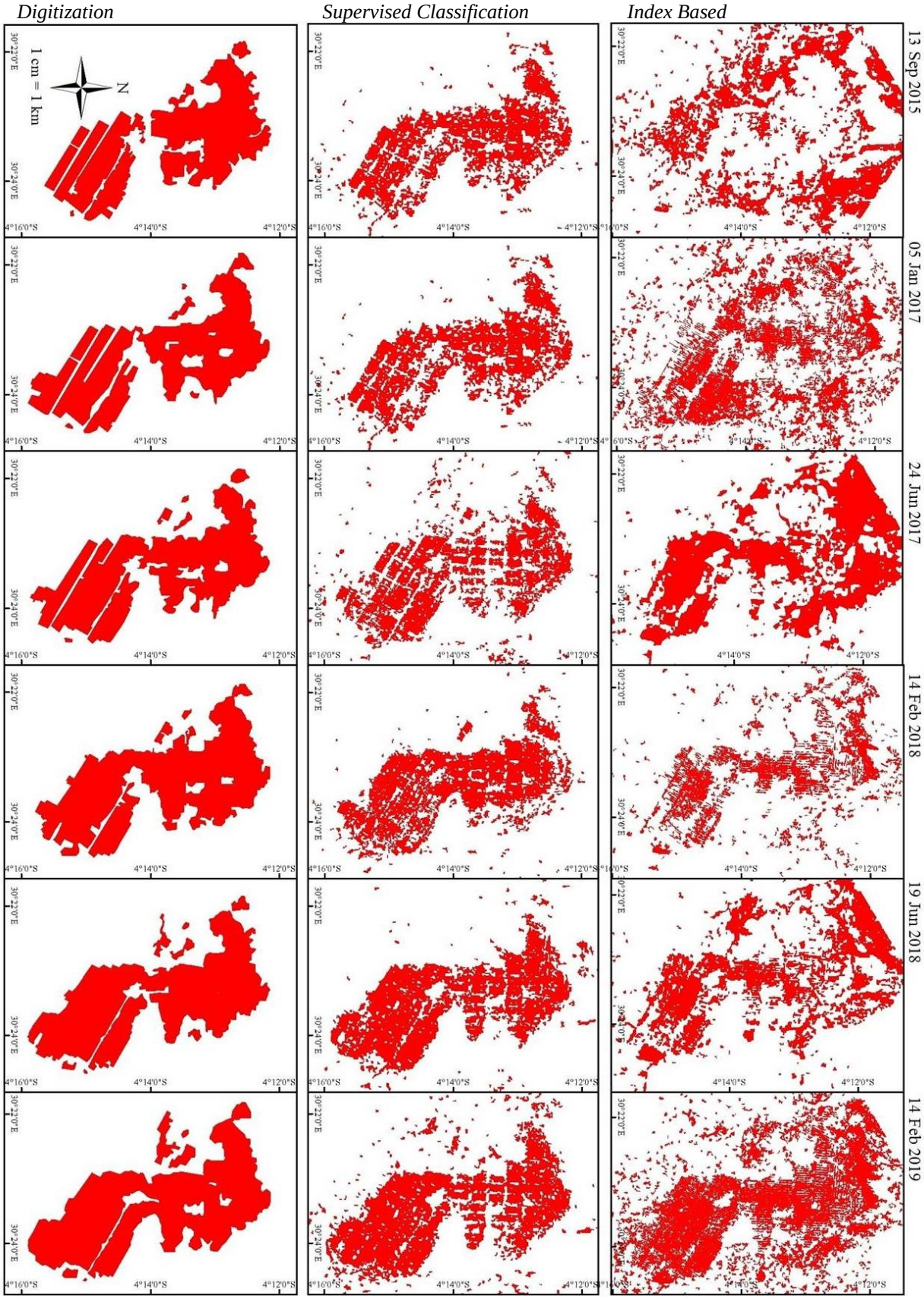

Figure A1: Time Series Nyarugusu. Six of the seven images of the time series are displayed. Each step in the time series is depicted individually.

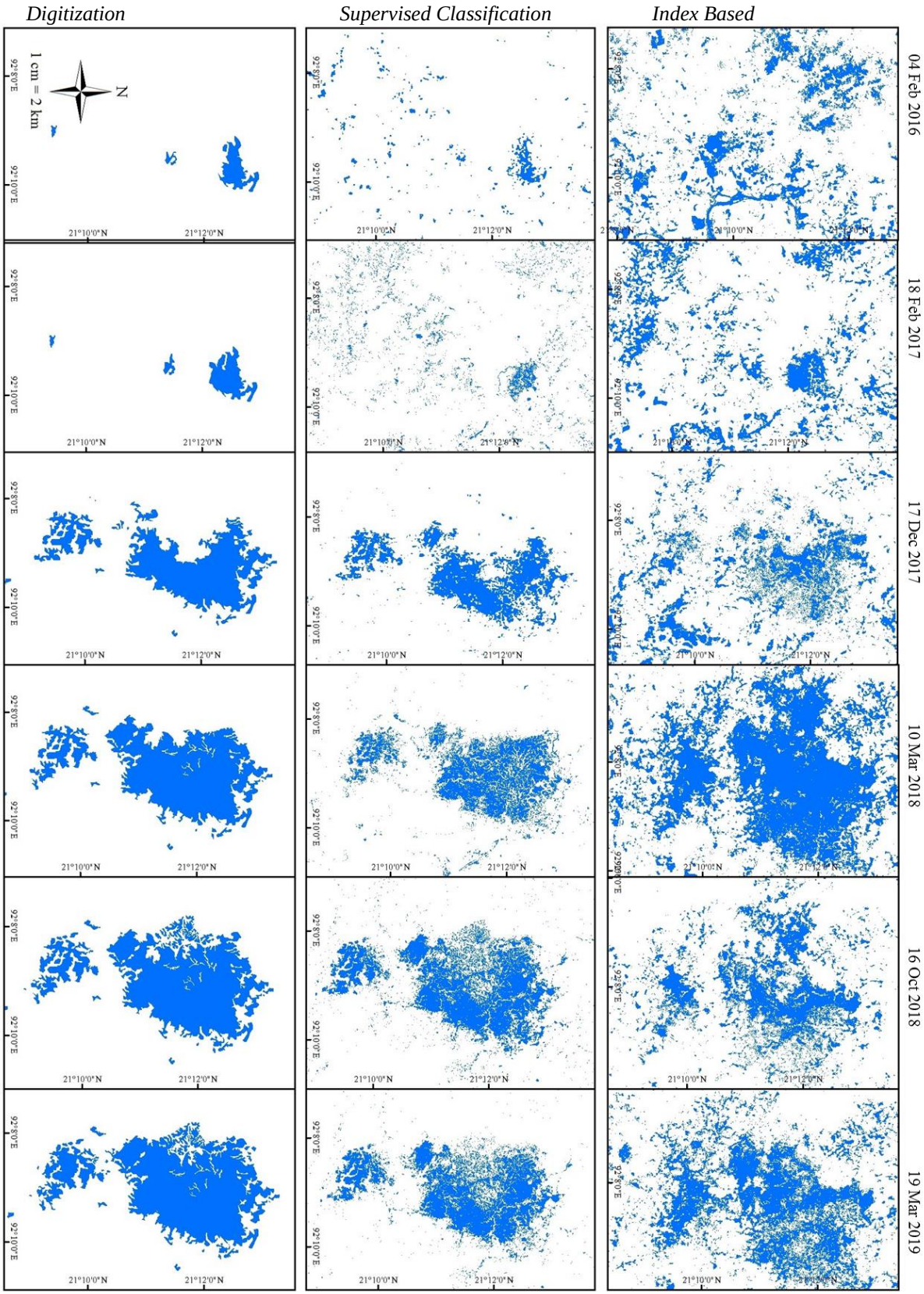

Figure A2: Time Series Kutupalong. Six of the seven images of the time series are displayed. Each step in the time series is depicted individually.

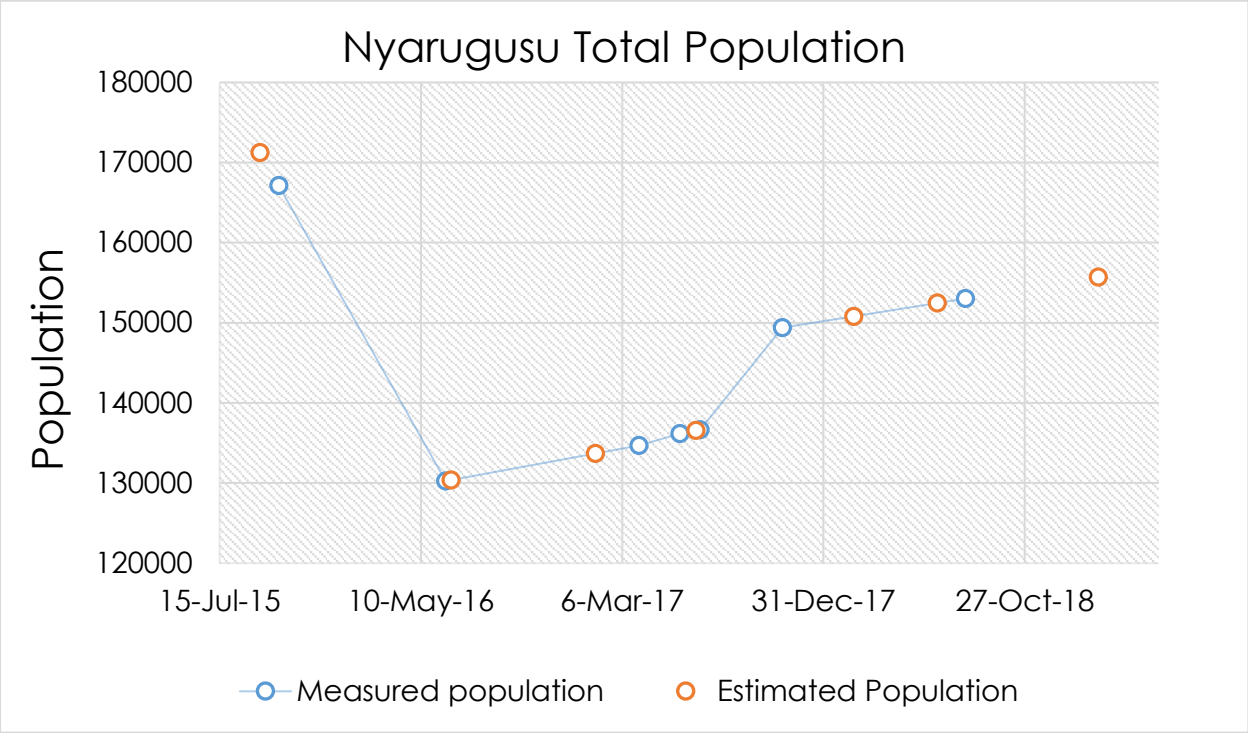

Figure A3: Nyarugusu Refugee Camp Population. The Measured population is the data measured by UNHCR in their reports while Estimated Population is the Interpolated data used for this study.

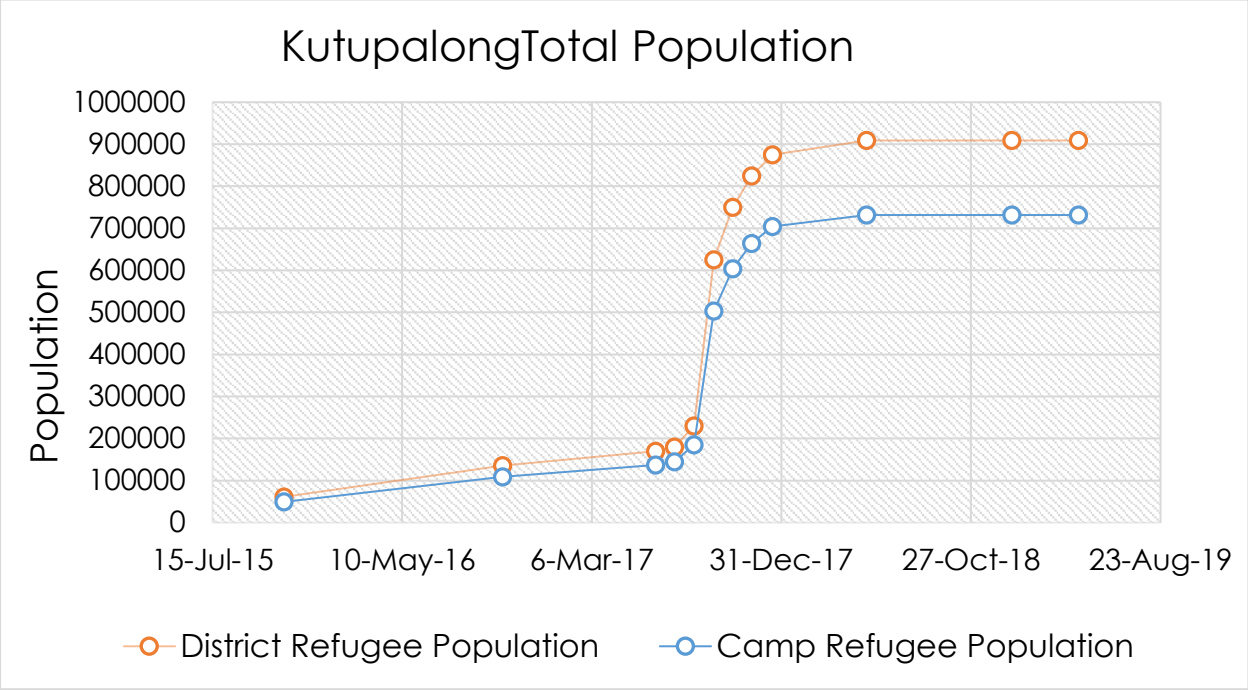

Figure A4: Kutupalong Refugee Camp Population. The District Refugee Population is the total population for the district while the Camp Refugee Population is the population of the camp estimated using the ratio between the two calculated for the last point of the series.