Understanding a Rapidly Expanding Refugee Camp Using Convolutional Neural Networks and Satellite Imagery

Susanne A. Benz
School of Global Policy and Strategy
UC San Diego
La Jolla,CA, USA
sabenz@ucsd.edu

Hogeun Park
School of Global Policy and Strategy
UC San Diego
La Jolla,CA, USA
hopark@ucsd.edu

Jiaxin Li
San Diego Supercomputer Center
UC San Diego
La Jolla,CA, USA
jil048@ucsd.edu

Daniel Crawl
San Diego Supercomputer Center
UC San Diego
La Jolla,CA, USA
lcrawl@ucsd.edu

Jessica Block
Qualcomm Institute
UC San Diego
La Jolla,CA, USA
j.block@eng.ucsd.edu

Mai H. Nguyen
San Diego Supercomputer Center
UC San Diego
La Jolla,CA, USA
mhnguyen@ucsd.edu

Ilkay Altintas
San Diego Supercomputer Center
UC San Diego
La Jolla,CA, USA
ialtintas@ucsd.edu

***Abstract*—In summer 2017, close to one million Rohingya, an ethnic minority group in Myanmar, have fled to Bangladesh due to the persecution of Muslims. This large influx of refugees has resided around existing refugee camps. Because of this dramatic expansion, the newly established Kutupalong-Balukhali expansion site lacked basic infrastructure and public service. While Non-Governmental Organizations (NGOs) such as Refugee Relief and Repatriation Commissioner (RRCC) conducted a series of counting exercises to understand the demographics of refugees, our understanding of camp formation is still limited. Since the household type survey is time-consuming and does not entail geo-information, we propose to use a combination of high-resolution satellite imagery and machine learning (ML) techniques to assess the spatiotemporal dynamics of the refugee camp. Four Very-High Resolution (VHR) images (i.e., World View-2) are analyze to compare the camp pre- and post-influx. Using deep learning and unsupervised learning, we organized the satellite image tiles of a given region into geographically relevant categories. Specifically, we used a pre-trained convolutional neural network (CNN) to extract features from the image tiles, followed by cluster analysis to segment the extracted features into similar groups. Our results show that the size of the built-up area increased significantly from 0.4 km^2 in January 2016 and 1.5 km^2 in May 2017 to 8.9 km^2 in December 2017 and 9.5 km^2 in February 2018. Through the benefits of unsupervised machine learning, we further detected the densification of the refugee camp over time and were able to display its heterogeneous structure. The developed method is scalable and applicable to rapidly expanding settlements across various regions. And thus a useful tool to enhance our understanding of the structure of refugee camps, which enables us to allocate resources for humanitarian needs to the most vulnerable populations.**

***Keywords*-Refugee Camp, Rohingya, Convolutional Neural Networks, Satellite Imagery, Machine Learning, Feature Extraction**

I. Introduction

In the weeks following August 25 2017, the continuous destruction of Rohingya villages in western Myanmar's Rakhine State caused a mass exodus to Cox's Basar District in south east Bangladesh [1]. While two United Nations High Commissioner for Refugees (UNHCR) camps, the Kutupalong refugee camp and the Nayapara refugee camp, have existed in this area since 1991 [2], the number of refugees soon exceeded their capacity significantly, and fleeing Rohingyas settled in makeshift camps in the surrounding area. This is now called the Kutupalong-Balukhali expansion site and is the world's largest refugee camp, with an estimated population of more than 900,000 people [3]. Conditions in the expansion site have been described as one of the worst slums imaginable, lacking access to water, hygiene and medicine [4]. A recent study from 2019 found an increased risk for field epidemics and noted among others a major outbreak of diphtheria [5]. At the same time, monsoon season makes the camp sites vulnerable to natural disaster including flash floods, strong winds and landslides [6].

One of the major challenges in managing the Rohingya displacement crisis is getting data on the dynamic structure in these informal settlements and the number of people in

978-1-7281-2451-3/19/$31.00 ©2019 IEEE
DOI 10.1109/eScience.2019.00034

need. Due to heterogeneity and dynamic nature of these informal settlements, our limited understanding of evolvement of this area restricted plausible policy implications [7]. A more nuanced characterization of informal settlements as evolving and heterogeneous structures would capture the socioeconomic and infrastructure needs among refugee camps. If this information is known, aid agencies are able to to respond in appropriate time and fashion. With this regard, a counting-housing exercise was performed by Refugee Relief and Repatriation Commissioner (RRRC) through a series of refugee family interviews in the Kutupalong-Balukhali expansion site [8]. In March 2018, a randomized survey was conducted in order to better understand demography of the camp and its host community [9]. While these studies offer a very detailed overview including gender- and age-disaggregated statistics, it is very time consuming and cannot easily detect temporal developments and does not include geo-spatial analysis.

Hassan et al. (2017) used a machine learning technique (i.e., Random Forest Classification) and Sentinel-2 imagery (10 m resolution) to map the extent of the refugee camp in December 2016 and 2017. They found an increase of more than 750% [10]. However, with a main focus on the environmental impact caused by the development of the refugee camp, such as the destruction of wildlife habitat and biodiversity, they offer limited information on the internal structure of and changes within the expansion site across time.

To better account for this complex process of refugee expansion, a more nuanced understanding can be achieved by a combination of Very-High Resolution (VHR) Satellite Imagery and a pre-trained convolutional neural network (CNN). This method was previously applied over rural areas in Liberia in order to detect educational facilities [11] and for demographic analysis [12]. Here the method will be applied to four images of the Kutupalong-Balukhali expansion site (i.e., two pre- and two post- influx), in order to answer the two fundamental research questions of this paper: (1) How much did the refugee camp expand spatially? And (2) Are there any patterns of internal development (i.e., densification, aggregation, etc)? To answer these research questions, we run cluster analysis twice: First to detect temporal development of the built up area and second, analysing build up areas only, to detect structural changes within camps. These results enabled us to answer remaining questions about the formation of infrastructure and structural development within the expansion site, giving new insight into the heterogenity of a rapidly expanding refugee camp. This approach will help identify the heterogeneous structure of refugee camps and potential entry points of intervention to alleviate emerging challenges.

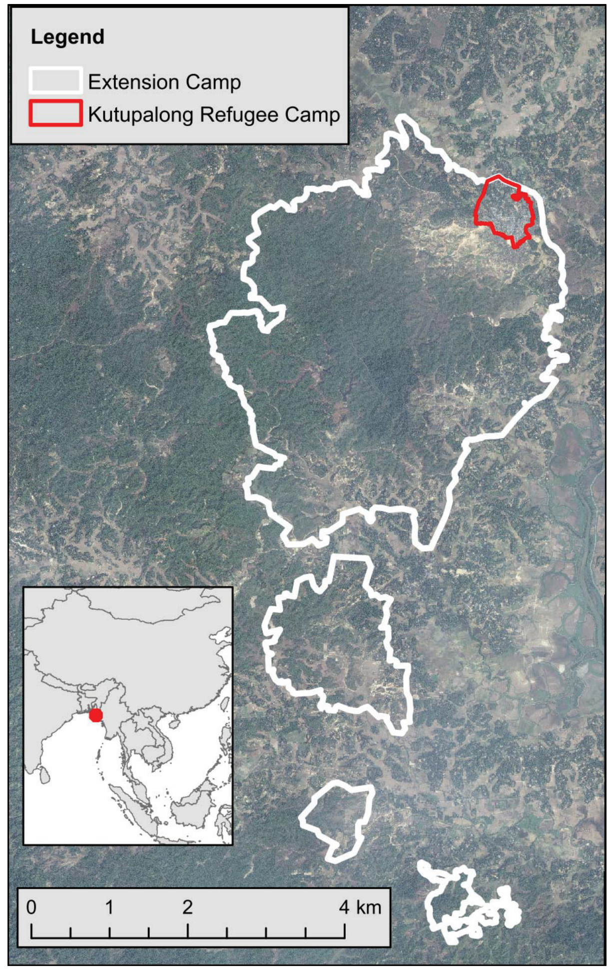

Figure 1. Location and set up of the Kutupalong-Balukhali expansion site. Background image from January 2016.

II. Data

A. Study Area

Our study area is the Kutupalong-Balukhali expansion site located in Cox's Bazar District, Bangladesh. The expansion site is structured in several camps, and the total extent is given in Fig. 1. Topography has been described as steep hillsides prone to mudslides and flash floods in monsoon season.

Counting exercises in the area have been performed by the RRRC that reported the drastic increase in population from less than 75,000 before October 2016 to more than 900,000 in February 2019 [8].

B. Very-High Resolution Satellite Imagery

We analyzed four Very-High Resolution (VHR) satellite images: three taken by World-View-2 and one from GeoEye-1 (Fig. 2). Imagery was made available through the Digital Globe Foundation [13] via their Geospatial Big Data

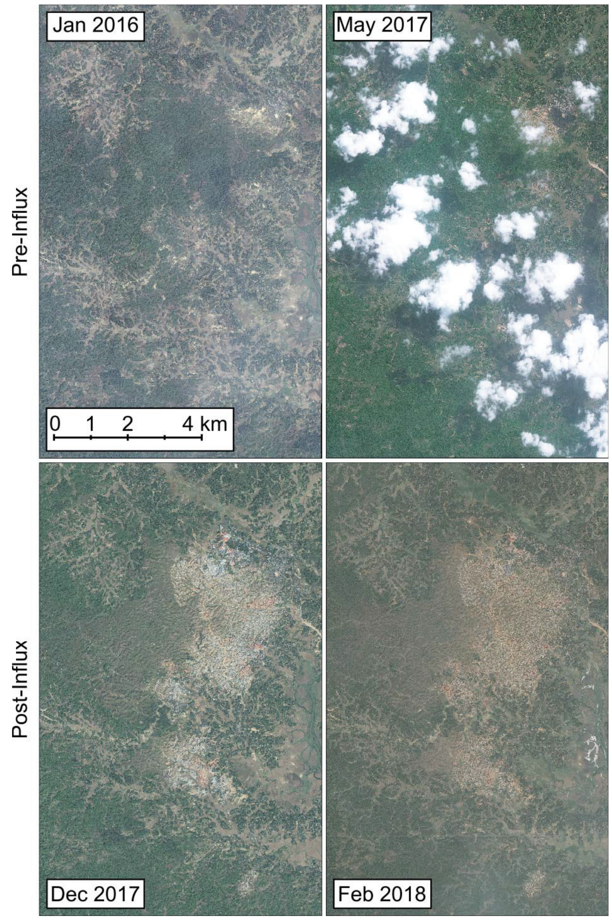

Figure 2. Imagery analyzed in this study. The upper two images show the study area before the influx of refugees in August 2017, the lower two images after influx.

Platform (GBDX) [14]. All images have a resolution of 0.5 m and are provided with the visible red, green, blue (RGB) spectral bands only. They are pre-processed and geo-referenced for immediate use.

The two images pre-influx were taken in January 27 2016 and May 25 2017. It is important to note that the May 2017 image is slightly cloudy and is the only image taken by GeoEye-1 instead of World-View-2. This results in different metadata such as viewing angle and processing. However, as it was the only available image between January 2016 and the influx of refugees in August 2017, we decided to keep the image in the analysis.

The two images post-influx were taken on December 29 2017 and February 13 2018. Due to monsoon season and persistent cloud cover, no cloud free or even partially cloudy image between August and December 2017 was available, and we are not able to monitor changes during these months more closely.

III. Method

A. Data Preparation

Each satellite imagery was sliced into tiles of 100 $\times$ 100 Pixel (50 $\times$ 50 m), creating a total of 37,884 tiles per image. To ensure comparability, all images were clipped to the same extent, within the uncertainty of geo-referencing, before slicing them into tiles. Therefore the area covered by each tile stays consistent for each analyzed image, and thus, point in time.

B. Machine Learning

Our approach uses deep learning and unsupervised learning to organize the prepared satellite image tiles of a given region into geographically relevant categories. Specifically, we use Convolutional Neural Networks (CNNs) and cluster analysis. A ResNet-50 [15] CNN pre-trained on ImageNet data [16] is used as a feature extractor to process the image tiles. That is, each image tile is input to the CNN, and features representing that tile are extracted from the last pooling layer ('pool5'), yielding a vector of 2048 features.

Cluster analysis is then applied to the feature vectors, which are normalized to have a mean of 0 and a standard deviation of 1. Cluster analysis is an unsupervised learning technique used to organize data elements into similar groups and does not require any labels to create the model. An unsupervised approach is needed for this application since ground truth, specifying for example the level of development for any given image tile, is not available. For our experiments, we use k-means for cluster analysis. In order to organize the resulting clusters so that visually similar clusters are closer together, the cluster centers are processed using principal component analysis (PCA) and sorted based on the first principal component.

The cluster model was generated using the set of images from December 2017. We used a two-step clustering process. In the first step, we sorted all images into four clusters (i.e., $k = 4$) in order to identify the four common land use types: build-up, agricultural, natural, and forest. In the second step, all tiles identified as built-up area in step one were clustered again, this time into seven clusters (i.e., $k = 7$). Here the number of clusters was determined through empirical testing. These seven clusters were then analyzed to determine different built-up categories. The cluster model was then applied to the other sets of images to organize those tiles into categories. Tracking how each image tile changed categories between the different data sets allowed us to analyze the change from non-built-up to built-up and the change among the built-up categories.

IV. Results and Discussion

A. Identifying built-up areas

All images were sorted into four clusters using tiles from December 2017 as a training set in order to detect the

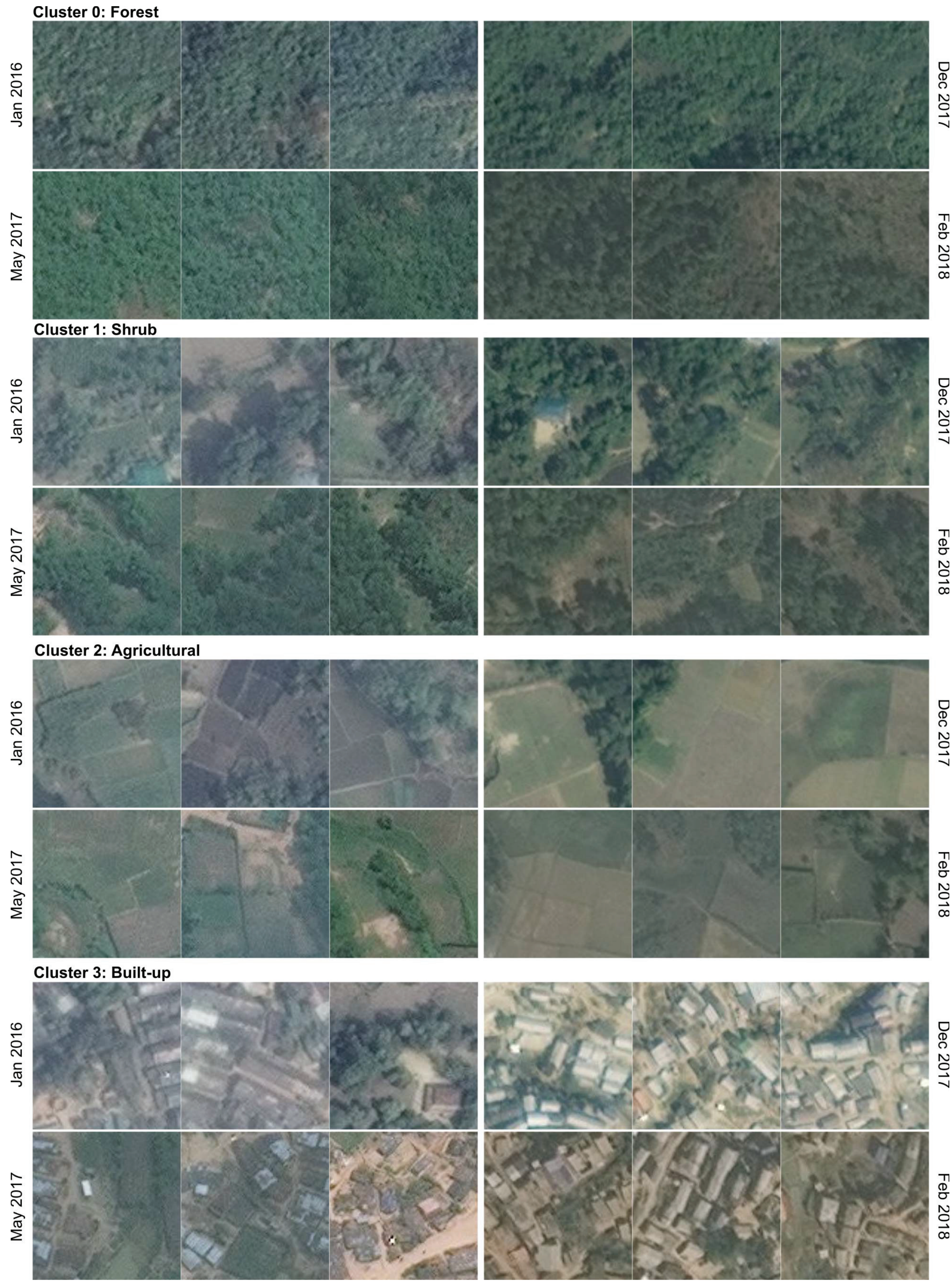

Figure 3. The three tiles closest to the corresponding cluster center for each cluster and each image.

Table I
PERCENTAGE OF TILES IN EACH CLUSTER OF THE INITIAL RUN OF FOUR.

	Pre-Influx		Post-Influx	
	Jan 2016	May 2017	Dec 2017	Feb 2018
Forest	39%	53%	32%	38%
Shrub	30%	24%	34%	23%
Agricultural	30%	21%	25%	28%
Built-up	<1%	2%	9%	10%

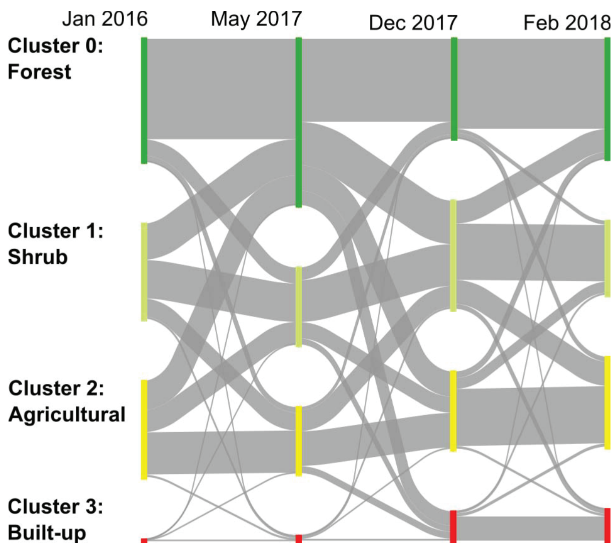

Figure 4. Sankey diagram [17] displaying the changes between the four original clusters (forest, shrub, agriculture, and built-up) for all analyzed times.

location of the built-up area. The four identified clusters are: Cluster 0, a homogeneous cluster primarily displaying **forest**; Cluster 1, here called **shrub**, displaying a mixture of different land cover types ranging from forest, fields and grassland to isolated buildings; Cluster 2, displaying **agricultural** areas and farmland; and Cluster 3, displaying **built-up** lands. For each image the three tiles closest to the corresponding cluster center can be found in Fig. 3. The percentage of tiles covered by each cluster is given in Table I. Although the data implies an increase in tiles sorted into the Forest cluster in May 2018, we can link this to the cloud cover (Fig. 2). While white in color, the uniform look of tiles covered by clouds lead to them being sorted into this cluster. Nevertheless, manual validation revealed no obvious errors in classification indicating that cluster detection from a model based on the December 2017 image is applicable to other images as well, regardless of preprocessing and color balance. This is particularly of interest for the imagery from May 2017, as it was taken by the satellite GeoEye-1 instead of World-View-2. Our approach therefore provides a useful tool to detect and display changes in a meaningful way (Fig. 3).

Overall, we detect an increase in built-up area from January 2016 to February 2018 of more than 2,000%, increasing from less than 0.5 km^2 to close to 10 km^2. In a study relying on Sentinel-2 imagery and random forest machine learning models, Hassan et al. (2018) found a growth rate of 835% between December 2016 and 2017 [10] over the same area. The different results are primarily caused by the chosen time period. Accordingly, our method detects a growth rate of approximately 600% between May 2018 and December 2018.

This increase in built up area is also visualized in the Sankey diagram [17] in Fig. 4. Here, the large fluctuations between forest, shrub and agriculture are likely caused by vegetation growth due to seasonal variations. Still, the increase in built-up area is most likely linked to a loss in agricultural land and forest area. This is further confirmed when mapping the detected clusters for all images (Fig. 5). We are able to detect that the increase in built-up area pre-flux between January 2016 and May 2017 occurred primarily in the original Kutupalong Refugee Camp, while the influx of refugees in August 2018 led to the construction of makeshift camps in the eastern part of the expansion site. It is important to note that within the extent of the original camp, the built-up area is replaced by shrub and farmland between May and Dec 2017. Upon closer inspection, this appears to be primarily caused by an increase in vegetation cover and again seasonal variations. However, a more detailed analysis, including additional images throughout the year, is necessary to validate these observations. While population between December 2017 and February 2018 did not increase significantly according to the conducted counting exercises, we are able to detect westward expansions, especially in the northern part of the camp.

B. Understanding the Internal Structure of the Camp

All tiles identified as built-up in step one of our process were clustered again in order to gain insights into the structural changes and evolution of the expansion site. In this step, the clustering algorithm was run with seven clusters. For the two post influx images, the three tiles closest to the corresponding cluster center are shown in Fig. 6. The first two clusters 0 and 1 display **densely built-up** locations with small houses and little to no vegetation. Clusters 2 and 3 are less densely built-up, here called **medium built-up**. They show slightly more vegetation than clusters 0 and 1 and often display larger buildings that might indicate infrastructure such as community centers, markets or hospitals. However, future research is necessary to validate these findings. The next cluster, cluster 4, appears to be defined by the **red roofs**, and the last two clusters 5 and 6 show a low building density with large parts of the tiles covered by vegetation or surface waters, here called **low built-up**. Again, building size is above average. As these low built-up tiles were dominant in the pre-influx images (Table II), we can conclude that they include settlements outside of the refugee camp.

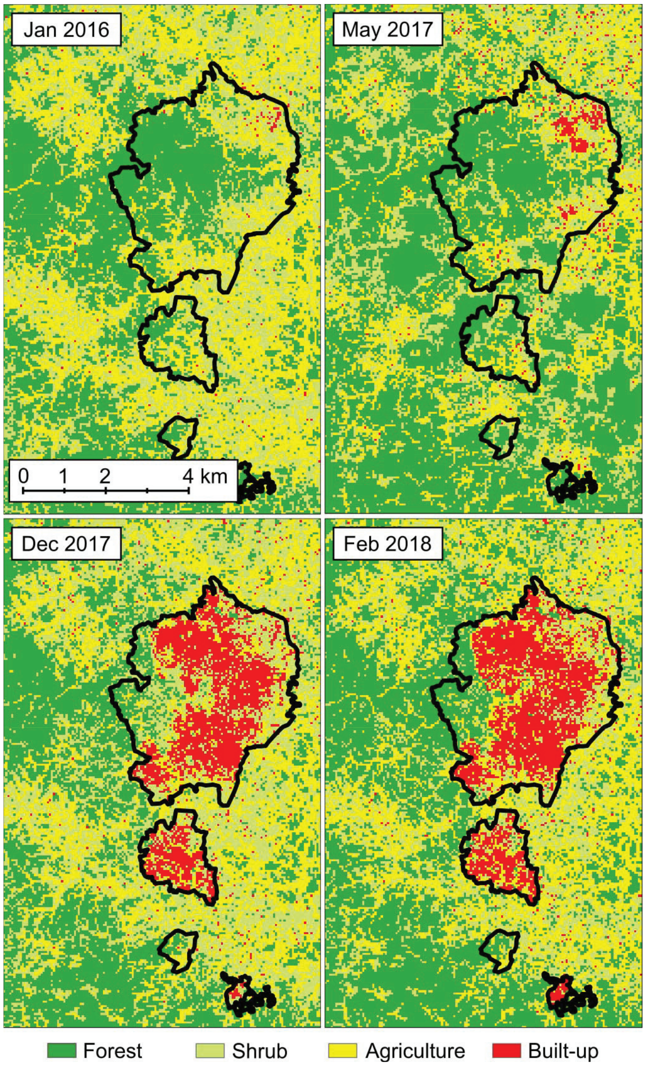

Figure 5. Map of the distribution of the four original clusters (forest, shrub, agriculture, and built-up) for each of the analyzed images. The border of the expansion site is given in black

Fig.7 displays a Sankey chart [17] showing changes between the two images from December 2017 and February 2018. Only tiles identified as built-up area in both images are analyzed. An increase in Cluster 1, densely built-up areas, and a decrease in Cluster 3, medium built-up areas, become apparently, indicating a densification of the existing refugee camp. At the same time, tiles that are sorted in the built-up cluster for the first time in February 2018, are more often sorted into cluster 3, medium built-up areas than tile that already where built-up before. (25% compared to 14% when analyzing all tiles in Table II). Additionally it appears that Cluster 4, primarily defined by buildings with red roofs, is shrinking. This change might be related to a simple change in color due to dust and fading colors from sun exposure (comp Fig. 6).

Densification of the camp can also be observed in the percentages of tiles in each cluster in Table II: In February 2018 densely built-up tiles make up 46% of the entire built-up area compared to 37% in December 2019. The spatial visualization of all clusters in Fig. 8 allows a more detailed analysis of the observed densification. We find that in December 2017, large areas of the expansion site, especially along the eastern border, previously covered by shrub and agricultural area, were primarily replaced by a homogeneous distribution of medium to low built-up tiles. In the February 2018 image, these tiles are partially sorted into densely build up clusters resulting in a much more heterogeneous camp with a high structure density.

It is of interest to note that the original Kutupalong refugee camp is primarily not sorted into the built-up cluster. While a densely built-up area center exists in the southwest region of the camp, most built-up tiles are isolated and primarily surrounded by agricultural and shrub land. This is caused by the small tile size of only 50 $\times$ 50 m detecting vegetable gardens associated with individual parcels.

At the same time, we can observe an extension of the camp area to the west, primarily consisting of low built-up clusters. In addition, tiles in this area are for the first time sorted into the agricultural cluster during the initial classification process, indicating the development of small-scale agriculture in the area. However, more detailed analysis including the seasonality of farming in Bangladesh is necessary to validate these findings.

Table II
PERCENTAGE OF TILES IN EACH CLUSTER OF RUN OF SEVEN FOCUSING ON BUILT-UP AREAS.

	Pre-Influx		Post-Influx	
	Jan 2016	May 2017	Dec 2017	Feb 2018
Cluster 0	17%	4%	17%	18%
Cluster 1	4%	8%	20%	28%
Cluster 2	11%	4%	15%	17%
Cluster 3	19%	36%	19%	14%
Cluster 4	0%	1%	10%	5%
Cluster 5	37%	28%	9%	10%
Cluster 6	12%	18%	9%	8%

V. CONCLUSION

Through a combination of satellite imagery and deep learning, we analyzed the expansion of Kutupalong-Balukhali refugee camp which has been mushroomed since summer of 2017 due to ethnic conflicts in Myanmar. Our study deepens the knowledge of the refugee camp's expansion as well as its structural changes by developing a scientifically robust method that classifies the campsite into ten clusters. Using deep learning and unsupervised learning, we first classified 50 $\times$ 50 m tiles of the images into four clusters: forest, shrub, agricultural and built-up, based on the same cluster model. Results show that our approach exceeds in detecting and displaying small scale changes in

Figure 6. The three tiles closest to the corresponding cluster center for each of the seven built-up clusters for the two post influx images.

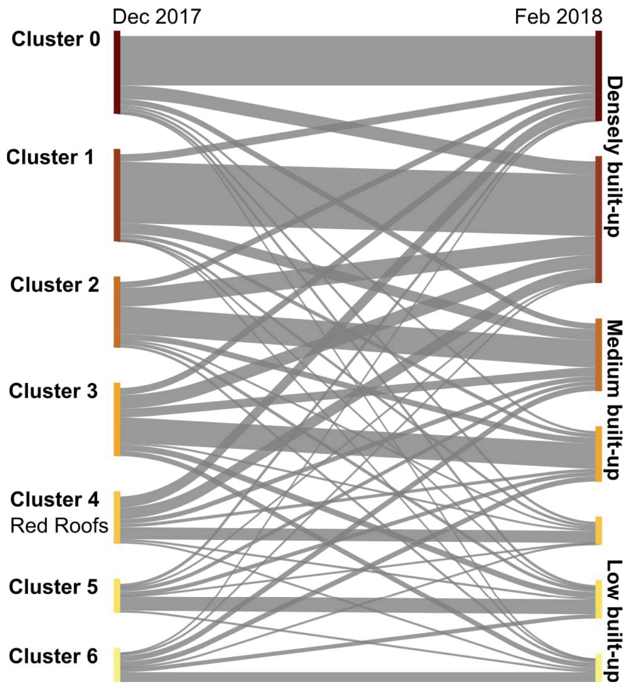

Figure 7. Sankey diagram displaying the changes between the seven built-up clusters for all images post influx.

a meaningful way, independent of preprocessing and color balance. We find that built-up areas increased tremendously from 0.4 km^2 in January 2016 to 9.5 km^2 in February 2018, primarily in the eastern parts of the expansion site.

In the second step, we analyzed built-up areas more closely by again classifying the corresponding tiles into seven clusters. This way, we were able to illustrate the structural changes within the camp from December 2017 to February 2018. Data indicate that structural density increases for most of the built-up area, especially in the eastern side of the expansion site. At the same time, newly developed low built-up settlements are located in the western areas of the camp. While we find several homogeneous areas with low to medium building density in the December 2017 imagery, in February 2018, the camp becomes more heterogeneous, developing features at a smaller scale. We identified two unique spatial patterns (i.e., aggregation and densification). As discussed in [18], the limited accessibility and availability of existing infrastructure have led incoming migrants to reside in areas close to pre- existing neighborhoods, which conclude the aggregation and densification.

While we successfully developed a novel technique to analyze dynamic changes of informal settlements, there is a room for development. In the future, we hope to extend this study with additional imagery taken after spring 2018 to help answer questions of the long-term structural development of rapidly expanding refugee camps such as the one in Bangladesh. Furthermore, in contrast to existing methods, our study does not rely on ground truth data. Hence, in the future, our method can be applied immediately to emerging refugee camps worldwide where it has the potential to help with the distribution of humanitarian aid in a timely manner to the most vulnerable people on this planet.

Acknowledgment

We would like to thank the Digital Globe Foundation for providing access to their data. This work was supported in part by NSF-1730158 for Cognitive Hardware and Software Ecosystem Community Infrastructure (CHASE-CI). Further we want to acknowledge the Big Pixel Initiative at the Center of Global Transformation at the University of California San Diego for supporting SAB and HP.

References

[1] Chris Beyrer and Adeeba Kamarulzaman, “Ethnic cleansing in myanmar: the rohingya crisis and human rights,” *The Lancet*, vol. 390, no. 10102, pp. 1570–1573, 2017.

[2] MARIJKE WIJNROKS, MARTIN W. BLOEM, NAEL ISLAM, HABIB RAHMAN, SWAPAN KUMAR DAS, ABDUL HYE, and GILLIAN HALL, “Surveillance of the health and nutritional status of rohingya refugees in bangladesh,” *Disasters*, vol. 17, no. 4, pp. 348–356, Dec. 1993.

[3] Steven OBrien and Mai Hosoy, “Bangladesh, operational update - 1 april 30 april 2019,” Tech. Rep., UN High Commissioner for Refugees (UNHCR), 2019.

[4] Kate White, “Rohingya in bangladesh: an unfolding public health emergency,” *The Lancet*, vol. 390, no. 10106, pp. 1947, 2017.

[5] Noore Alam, Bernadette Kenny, Julia E Maguire, Samuel McEwen, Meru Sheel, and M. Ximena Tolosa, “Field epidemiology in action: an australian perspective of epidemic response to the rohingya health emergencies in cox’s bazar, bangladesh,” *Global Biosecurity*, vol. 1, no. 1, pp. 119, Feb. 2019.

[6] Sophie Cousins, ““people will die” as monsoon approaches rohingya refugee camps in bangladesh,” *BMJ*, p. k2040, May 2018.

[7] Kathryn P Hacker, Karen C Seto, Federico Costa, Jason Corburn, Mitermayer G Reis, Albert I Ko, and Maria A Diuk-Wasser, “Urban slum structure: integrating socioeconomic and land cover data to model slum evolution in salvador, brazil,” *International Journal of Health Geographics*, vol. 12, no. 1, pp. 45, 2013.

[8] “Bangladesh refugee emergency population factsheet (as of 28 february 2019),” Tech. Rep., UN High Commissioner for Refugees (UNHCR), 2019.

[9] Abhishek Bhatia, Ayesha Mahmud, Arlan Fuller, Rebecca Shin, K.A.M Morshed, Azad Rahman, Tanvir Shatil, Mahmuda Sultana, Satchit Balsari, and Jennifer Leaning, “A rapid needs assessment among the rohingya and host communities in cox’s bazar, bangladesh: a randomized survey,” *OSF Preprints*, 2018.

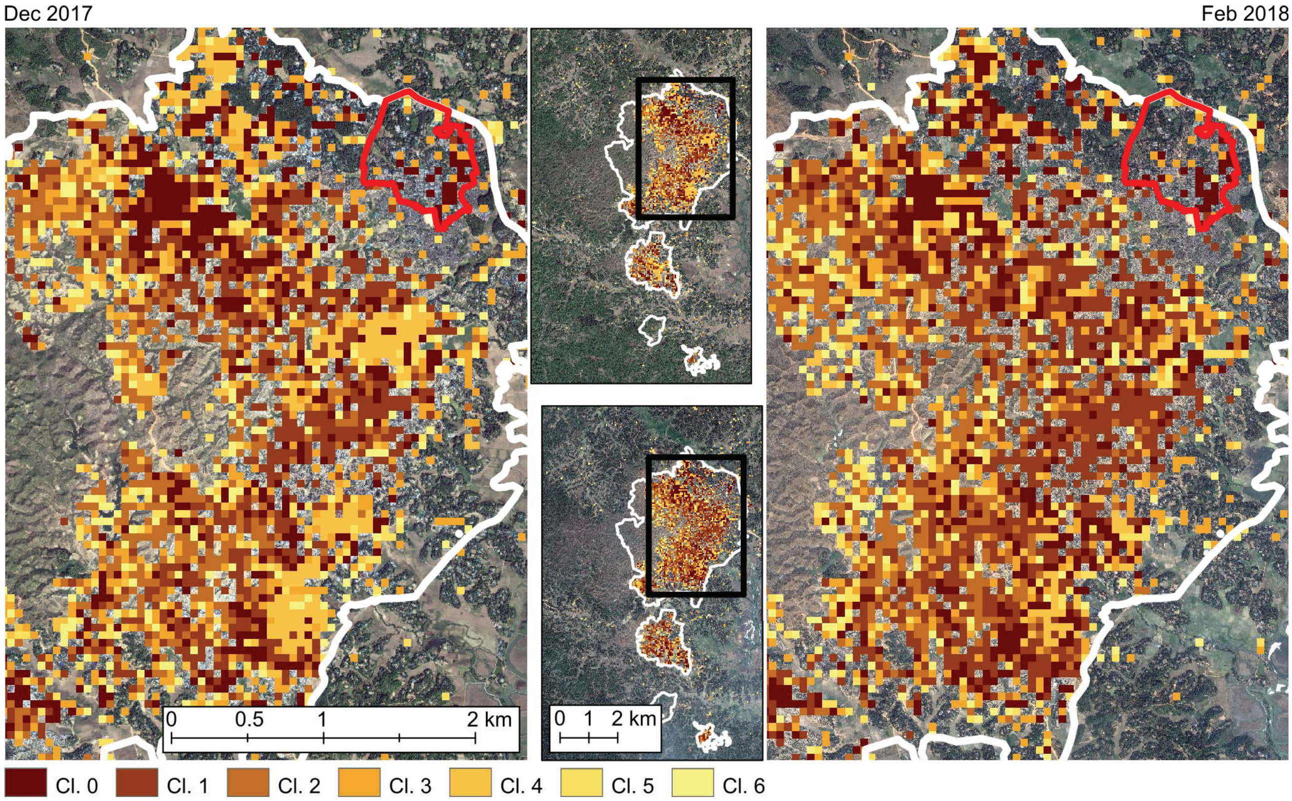

Figure 8. Map displaying the distribution of the seven build up clusters. Full images are shown in the middle panels, whereas the outer images zoom into the center of the extension camp. The extent of the expansion site is given in white, the extent of the original Kutupalong refugee camp in red.

[10] Mohammad Hassan, Audrey Smith, Katherine Walker, Munshi Rahman, and Jane Southworth, "Rohingya refugee crisis and forest cover change in teknaf, bangladesh," *Remote Sensing*, vol. 10, no. 5, pp. 689, Apr. 2018.

[11] Mehrdad Yazdani, Mai H Nguyen, Jessica Block, Daniel Crawl, Naroa Zurutuza, Dohyung Kim, Gordon Hanson, and Ilkay Altintas, "Scalable detection of rural schools in africa using convolutional neural networks and satellite imagery," in *2018 IEEE/ACM International Conference on Utility and Cloud Computing Companion (UCC Companion)*. IEEE, 2018, pp. 142–147.

[12] J. Block, M. Yazdani, M. Nguyen, D. Crawl, M. Jankowska, J. Graham, T. DeFanti, and I. Altintas, "An unsupervised deep learning approach for satellite image analysis with applications in demographic analysis," in *2017 IEEE 13th International Conference on e-Science (e-Science)*, Oct 2017, pp. 9–18.

[13] "Digital globe," https://www.digitalglobe.com/, 2018.

[14] "Gbdx platform - digital globe," https://platform.digitalglobe.com/gbdx/, 2018.

[15] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, "Deep residual learning for image recognition," *arXiv preprint arXiv:1512.03385*, 2015.

[16] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei, "Imagenet: A large-scale hierarchical image database," in *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*. IEEE, 2009, pp. 248–255.

[17] R. C. Lupton and J. M. Allwood, "Hybrid sankey diagrams: Visual analysis of multidimensional data for understanding resource use," *Resources, Conservation and Recycling*, vol. 124, pp. 141–151, 2017.

[18] Jean-Claude Bolay, "Slums and urban development: Questions on society and globalisation," *The European Journal of Development Research*, vol. 18, no. 2, pp. 284298, 2006.