Urban Sprawl Analysis in Kutupalong Refugee Camp, Bangladesh

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Abstract: Urban sprawl is a common phenomenon associated with geographical and political challenges such as refugee settlements and environmental extremes. Urban sprawl related to refugee or habitation settlement has been an area of active interest because of humanitarian and environmental problems. For example, higher rates of urban sprawling are positively correlated with higher rates of deforestation. The present study explored the viability and reproducibility of different classification techniques in assessing urban sprawl among Rohingya refugees in the Kutupalong refugee camp in Bangladesh. These classification methods include the Support Vector Machine (SVM) and Maximum Likelihood Classifier (MLC). The urban sprawl was measured based on the classification of urban and non-urban classes. The SVM yielded better overall accuracy performance compared to MLC classification. The study showed that urban class exhibited exponential growth from 2.01 km^2 to 5.37 km^2 within nine months. On the contrary, the non-urban class shrunk from 12.58 km^2 to 9.95 km^2 during the same period due to a high influx of refugees and rapid camp expansion.

1 INTRODUCTION

Remote sensing has become popular in the field of humanitarian action because it is an independent and reliable source of information that allows both a quick response to emergencies and monitoring of gradual changes that are associated with human settlements, including rehabilitation, sprawling, migration, and refuge (Lang et al., 2020, Braun et al., 2016 ; Blaschke et al., 2014 Lang et al., 2015). Remote sensing is extremely important when observations in the field are not possible manually due to limited budget, legal barriers, and security aspects (Chen, n.d.). The observation of specific places from space is not only crucial for decision making involving responses to natural disasters and emergencies concerning the human race but also helps to develop a general understanding of an area and the way trends and temporal dynamics have shaped the special and spatial patterns (Chang et al., 2011; Bello & Aina, 2014).

Approximately one million refugees of the Rohingya minority population in Myanmar crossed the border to Bangladesh seeking shelter from a systemic operation and prosecution (Faye, 2021). This caused significant expansions of the Kutupalong refugee camp within two months and a reduction in the vegetation in surrounding forests. Different humanitarian and Human Rights Organizations demanded frameworks camp monitoring and environmental impact analysis (Sahana et al., 2019). The refugee camp is situated in Ukhia, CoxBazar, Bangladesh. The oppressions and extortions of the Rohingya refugees caused the Kutupalong refugee camp to expand (Braun et al., 2019a)The refugee camps nowadays are more permanent than simple transitory settlements, therefore are considered as urban areas. The variables such as size, population density, layout, infrastructure concentration, socio-occupational profile, and trading activities are supporting factors to consider refugee camps as urban areas (Montclos & Kagwanja, 2000). The present work provides novel information by exploring the urban sprawl dynamics of the Rohingya refugees at the Kutupalong refugee camp through remote sensing techniques.

The research question focuses on how urbanization has changed following the outbreak of the Rohingya emergency by analysing four (4) drone

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images from 2017 and 2018, by answering the following questions:

1. Which machine learning classifier technique yields better performance in urban sprawl classification in the Refugee camp context?
2. How much km^2 has urban class increased over the period of 9 months in Kutupalong Refugee Camp?

2 DATA AND METHODS

2.1 Study Area

Kutupalong refugee camp is located in south-eastern Bangladesh along the border with Myanmar. The camp administrative area is defined by the following coordinates 21.2126°N 92.1634°E, and with a total area of 14.5 km^2, it hosts a population of 860,356 registered refugee individuals and 187,423 families (as of June 30, 2020, UNHCR). When Rohingya minority left Myanmar's adjacent Rakhine state as a consequence of religious and ethnic persecution, which culminated in brutal crackdowns and systematic executions beginning on August 25, 2017, Kutupalong became the world's biggest refugee camp. The study area in this research focuses on Kutupalong camp and its extensions located in Ukhia Upzalla in the district of Cox's Bazar region and its extensions. Figure 2 below represents the study area.

Kutupalong area is situated on a mix of plains and small hills, extending into the Chittagong Hill tracts bordering Myanmar. The area is characterized by heavy rain on the Chittagong Hill tracts has resulted in numerous landslides. The administration of the district has introduced a policy on restricted tree-cutting to limit erosion in the hope of limiting further landslides and related fatalities (Braun et al., 2019b).

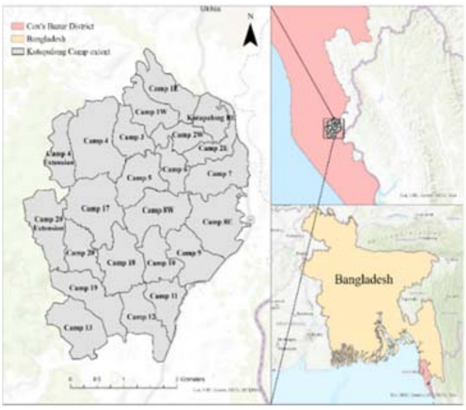

Figure 1: Study Area.

2.2 Data

The methodology for the present study included the acquisition of the images from IOM Bangladesh – Needs and Population Monitoring (NPM) Cox's Bazar Rohingya Refugees Settlements UAV Imagery, which were stored at data.humdata.org. The retrieved image packaged were downloaded in tiff format with mosaiced images. The images were combined and georeferenced, with Red, Blue, and Green bands. The dates of the images were taken from December 2017 to February, July, and September 2018 following the outbreak of violence in August 2017 in Rakhine State, Myanmar. The Imagery type is UAV with a resolution of 10 cm, projection WGS84 _Zone 46 N. While there were images from the entire Cox's Bazar Refugee and different camps stored in the repository, this research only focuses on the Kutupalong camp, located in Cox's Bazar region. The information on flight altitude and swath with is unknown to researchers.

The spatial database in shapefile format with an outline of camps, settlements, and sites where Rohingya refugees are staying in Cox's Basar has been acquired from data.humdata.org provided by the Inter Section coordination Group. The database contains the camp-block boundary (admin level-2 or camp sub-division) of Rohingya refugees in Cox's Bazar, Bangladesh. Since the research is excluding the remaining camps of in Cox's Bazar disrtirct, the shapefile was clipped leaving out only the Kutupalong camp and its extensions.

The shapefile of the study area is divided per camp into 23 sub-regions (polygons) with a total area consisting of 14.5 km^2. The biggest camp is Camp 4 with an area of 1.15 km^2 being on the northwest side of the study region to the smallest being camp 6 on the mid-eastern side with 0.36 km^2.

2.3 Methods

The diagram in Figure 2 explains the workflow of the research. The study is based on four different images from 4 different dates to analyse urbanization within the area of sprawl. Moreover, this research explores different remote sensing supervised classification methods (Support Vector Machine and Maximum Likelihood Classification) to assess which performs better analysing urbanization in refugee settlements.

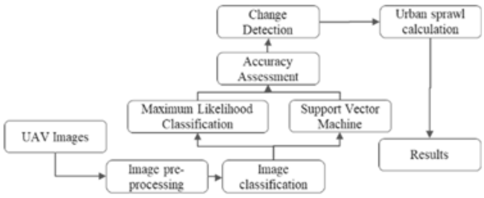

Figure 2: Data and methodology used for image classification and result validation.

2.3.1 Supervised Classification

The suggested technique consists of two-different classification assessments. The performance of various classifiers with found distinct dataset combinations from different dates in the same study area, to determine which of the two will yield superior results for urbanization. As one of the aims of the research is to understand which supervised classification provides the best results for mapping the urbanization in refugee settlements, MLC and SVM were tuned in.

To detect and understand urbanization, the authors have decided to create two classes – Urban and Non-Urban. Table 1 explains the categories and definitions of the classes:

Table 1: Classification nomenclature.

Class	Level 1 class	Description
Urban	Residential	Refugee housing units
	Commercial	Residential areas
	Industrial	Warehouses
Non-Urban	Agriculture	Farmlands
	Green Space	Grasslands, shrublands
	Waterbody	Natural or artificial waterbodies
	Undeveloped	Vacant land, bare land or land under construction

2.3.2 Image Classification Accuracy

When evaluating the effectiveness of a classification model applied to remote sensing data, accuracy measures are used to determine how near the model's predictions are to reality. As a result, accuracy evaluation compares the predicted labels assigned to an item using an MLC to its actual label using ground-truth data (test dataset).

A confusion matrix (or error matrix) is commonly used to determine classification accuracy. The classification accuracy is a confusion matrix table shows a correspondence between the classification result and reference image (images being ground truth data in this research). This enables for more in-depth examination than a simple fraction of the right classifications (accuracy). If the data set is imbalanced, that is, when the number of observations in various classes varies considerably, accuracy will produce false results (Maxwell & Warner, 2020)

From the confusion matrix, and following research development, we can compute several accuracy metrics, such as:

- Overall Accuracy: calculated by summing the number of correctly classified values and dividing by the total number of values.
- User's accuracy: The probability is calculated by dividing the number of properly predicted values by the total number of values projected to belong to a class. The user's accuracy is from the standpoint of the map user.
- Producer accuracy: The number of properly identified pixels in each category (on the major diagonal) divided by the number of reference pixels "known" to be of that category yields the following results (the column total).
- Kappa Coefficient: The kappa coefficient assesses the degree of agreement between categorization and truth values. A kappa value of one indicates complete agreement, whereas a value of zero indicates no agreement.

2.3.3 Urban Sprawl Analysis with Shannon's Entropy

The study aims to analyze the process of the built-up campsites over a period of 9 months in Cox's Bazaar, Bangladesh. While there is a wide variety of metrics that are used to measure the degree of urban sprawl, this research has adopted the Shannon's Entropy Index. The Shannon Entropy is an index or indication, which is capable of computing spatial concentration or dispersion in any spatial unit. The entropy values vary from 0 to 1, which 0 means that entropy values are maximally concentrated in one region, while 1 means that values are unevenly dispersed across space. The entropy value increases as built-up regions are dispersed from a city core or road network. This demonstrates whether the urban growth is more scattered or dense (Tewolde & Cabral, 2011). The model is calculated using the formula below:

$$Hn = -\sum_{i=1}^{n} pi \log(1/pi)/\log(n)$$

Where $pi = xi / \sum_i^n xi$ and xi is the density of land development, which is equal to the amount of built-up land divided by the total amount of land in the ith of n total zones.

3 RESULTS

3.1 Support Vector Machine

We have deployed ArcGIS Pro for supervised image classification. Support Vector Machine (SVM) supervised classification has been performed over the 4 UAV Images from the Kutupalong Refugee Camp region from 4 different dates to detect urban sprawl and camp expansion. Since Analysing UAV images with high resolution requires stronger computing power, and after multiple failed attempts to perform SVM classification using original resolution, the image size was reduced using resample function in ArcGIS Pro to X being 0.5 and Y being 0.5. When resampling the image, we understand that the resolution of the file with be altered, however since computational power was limited we have decided to accept the risk.

Image segmentation is a key component in object-based classification workflow. The segmented images produced have grouped neighboring pixels together, that are similar in color and shape. The segmented images produced for 4 different dates were acceptable. Following acceptance of segmented images, the training samples for 2 classes were collected for urban and non-urban classes. SVM has been performed with default 500 maximum number of samples per class, with active chromaticity color and means digital number activated.

Maps in Figure 3 are outputs of SVM supervised classification. The red polygons are representing urban areas, while the grey ones are non-urban.

Table 2 SVM: Representing the numbers of square kilometers (km^2) for each of the classes on each date.

Class/Date	24-12-17	12-02-18	31-07-18	24-09-18
Urban	2.01	2.91	4.63	5.37
Non-Urban	12.58	11.68	9.22	9.95

Upon completion of classification, the researcher will calculate the actual classified areas in square kilometers from all the 4 map outputs to compare the results. Firstly, the SVM classified maps will be converted to vector layer that is shapefile, using reclassified and export raster to polygon functions. Upon conversion, using polygons that have the same class were merged Calculate Geometry Attributes function was performed in order to n calculate the total square kilometer area of each class and compare between the dates.

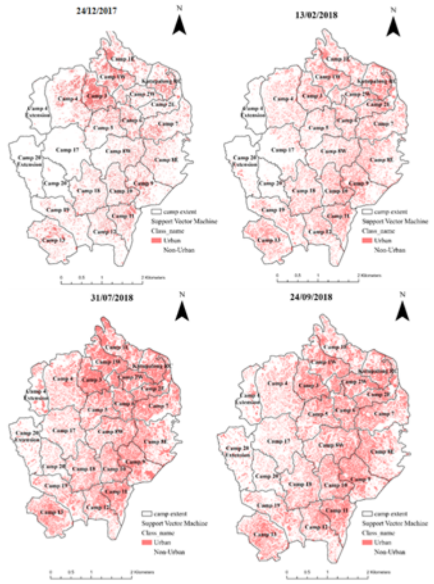

Figure 3: Support Vector Machine - Kutupalong Refugee Camp.

Area wise statistics has been calculated in ArcGIS Pro with above table 2 representing a number of km^2 for four different dates for each of our classes, we can conclude that the urban class has an exponential growth for only around 9 months from 2.01 km^2 on the first image of 24/12/2017 to 5.37 km^2 on the last image of 24/09/2018, which reads 13.7% of the total area on the first image to 35% total on the last image taken. The non-urban class however has reduced from 12.58 km^2 to 9.95 km^2 (from 86 % of the total area to 65%). The SVM classifier is showing higher are for non-urban class on 31-07-18 date compared to 24-09-18 date (9.22 km^2 to 9.95 km^2)

Even though the time span of the 3rd and 4th image is not the longest (2 months compared to 2nd and 3rd image which is around 5 months) we can notice the highest growth of urban class between 31-07-18 and 24-09-18, from 4.63 km^2 to 5.37 km^2.

3.2 Maximum Likelihood Classification

MLC has been performed over the four images from different dates in the study area. Following the same methodology as for the SVM classifier, the researcher is interested to see the urbanization over the study area in Kutupalong Camp, Bangladesh, two different classes were used – Urban and Non-Urban. Training samples in form of polygons were collected for each class as follows. The MLC showed good performance in classifying very high spatial resolution images as it was not failing during the classification run process, unlike the SVM classification. However, to fairly compare the two classifications, we performed the MLC classification with resampled in order to fairly compare the classification performances.

The maps in Figure 5 below are the results of supervised classification using a Maximum Likelihood Classification. The blue polygons indicate the classified urban class over the study area.

After classification is complete, the actual classified area in square kilometers for all four maps has been calculated, to understand the classification by calculating the geometry attributes of urban and non-urban classes.

Table 3: Representing a number of square kilometers (km^2) for each of the classes on each date.

Class/Date	24-12-17	12-02-18	31-07-18	24-09-18
Urban	3.2	3.6	5.25	7.8
Non-Urban	11.3	10.9	9.25	6.7

Unlike in the case of SVM, with MLC we can understand that the most significant change in terms of urban class expansion is between the third and last image dates (31-07-18 to 24-09-18), which percentage-wise gives an increase from 36% of the total area on the third image, to 54% of the total area. In the case of the non-urban class, the same timespan (31-07-18 to 24-09-18) gives the highest decrease in terms of the area from 9.25 km^2 to 6.7 km^2 (percentage-wise this gives us a decrease from 64% to 46%).

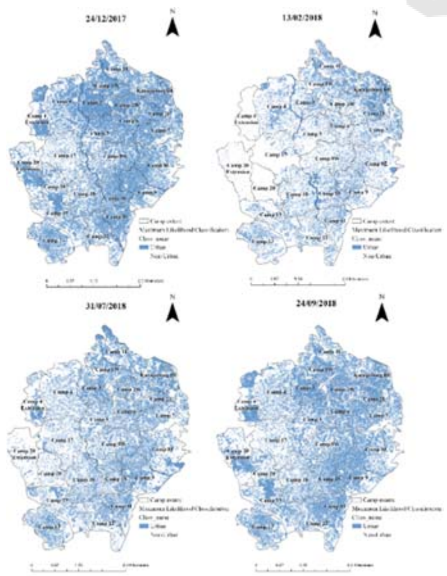

Figure 4: Maximum Likelihood Classification - Kutupalong Refugee Camp.

3.3 Accuracy Assessment

The main goal of the research is to evaluate the performance of the two classifiers over the different time periods and to determine which of the classifiers produces superior results.

For each of the classified images (SVM and MLC) the random 100 points have been computed in ArcGIS Pro in order to get the accuracy metrics. The related UAV image for each date has been used for ground truth testing against the 100 random points produced. After the ground truth comparison with classifiers, confusion matrices have been computed to get overall accuracy, user accuracy, producer accuracy, and Kappa Index of agreement.

The results indicate that both classifiers scored high overall accuracy and performed well when classifying UAV imagery in an environment such as refugee camp settlements.

Table 4: Confusion Matrix - Support Vector Machine.

Class/ Date	24-12-17		13-02-18		31-07-18		24-09-18	
	OA=85%		OA=90%		OA=94%		OA=83%	
	UA	PA	UA	PA	UA	PA	UA	PA
Urban	100%	48%	90%	69%	96%	91%	91%	67%
Non-Urban	83%	100%	90%	97%	94%	97%	79%	95%
Kappa	0.57		0.72		0.89		0.64	

The overall accuracy yielded good results for the SVM classifier, having a minimum value of 83% and a maximum value of 85%. User accuracy and producer accuracy also showed favorable results, with exception of 48% of producer accuracy of urban class for the first date of SVM classified image. The kappa coefficient and the degree of agreement between categorization and truth values vary from 0.57 for the first image to 0.89 for the third image.

Table 5: Confusion Matrix - Maximum Likelihood Classification.

Class/ Date	24-12-17		13-02-18		31-07-18		24-09-18	
	OA=81 %		OA=86 %		OA=87 %		OA=85 %	
	UA	PA	UA	PA	UA	PA	UA	PA
Urban	86 %	54 %	84 %	68 %	72 %	90 %	76 %	90 %
Non-Urban	79 %	95 %	87 %	94 %	95 %	86 %	93 %	82 %
Kappa	0.54		0.65		0.71		0.69	

Maximum Likelihood Classification has produced similar results in comparison to SVM classified. The minimum overall accuracy is 81% for the first image and varies to a maximum of 87% for the third image. User accuracy and producer accuracy have shown good scores however slightly less when in comparison to the SVM classifier. The Kappa coefficient and degree of agreement between categorization and true values is varying from 0.54 for the first image to 0.71 for the third image.

3.4 Change Detection: Support Vector Machine

To visualize the urban sprawl and detect changes between the dates, Change Detection Wizard of ArcGIS Pro has been utilized. The categorical change method of change detection has been configured over the 4 classified raster images. Processing was set to the full extent and class configuration is as follows:

- From Classes: Non-Urban
- To Classes: Urban and Non-Urban

This would give us the outputs where Non-Urban pixels have changed to Urban class, and where Non-Urban Class did not change. The smoothing Neighbourhood was set to none. Figure 4 represents the change analysis of subsequential images from the first to the last date.

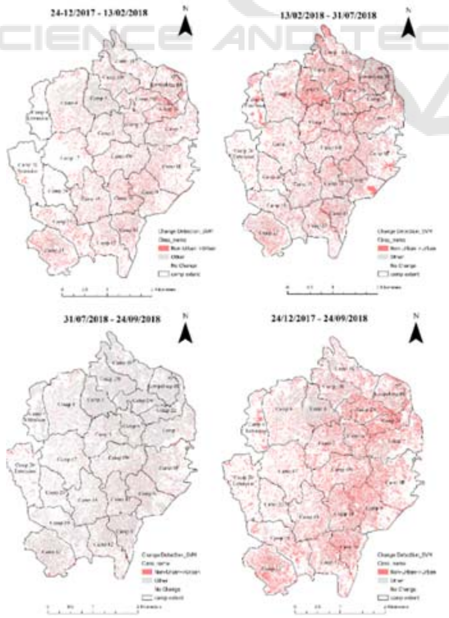

Figure 5: Change Detection Maps - Support Vector Machine.

With overlaying the study area extent which has information on sub-camps and the classified raster image, we can compute the camp-wise statistics of SVM supervised classification for four (4) different dates, to understand the direction urban sprawl is taking.

In terms of urban class, Camp 3, Camp 1W, Kutupalong RC, and Camp 6 had the highest value of urban class on the first image (24/12/2017) with 53%, 32%, 25%, and 23% respectively, while in the case of the last image (24/09/2018) Camp 10, Camp 11, Camp 12 and Camp 13 showed highest values of urban class with 70%, 59%, 58%, and 57% respectively. However, the highest increase of urban class within camps compared between the first and the last image can be noticed in Camp 10, Camp 11, Camp 12, and Camp 13 with an increase of 45%, 43% 33%, and 32% respectively. These camps that show the highest change in terms of urbanization are all located in the south of the study area.

3.5 Shannon's Diversity Index

Shannon's Diversity Index shows us species diversity in the community. In the context of this research, it is giving us an understanding of the urban sprawl composition and class richness and evenness over time (Bourne & Conway, 2014). The diversity index of the urban class for SVM classifier for dates 24-12-2017, 13-02-2018, 31-07-2018 and 24-09-2018 0.4 , 0.5 , 0.65 and 0.62 respectively. The trend of results of Shannon's diversity index for both classifiers shows lower diversity between the first two image dates, however, it has an exponential growth in value for the third and fourth dates. This has shown that the urban sprawl in the Kutupalong refugee camp has increased, due to the influx of refugees and urban expansion as a need for more housing. If the urban class is unevenly distributed throughout space, the increased value of Shannon's Diversity index reflects that (K. Madhavi Lata et al., 2009).

Table 6: Evolution of Shannon's Diversity Index for MLC and SVM Classifier.

Date/ Classifier	24/12/17	12/02/18	31/07/18	24/09/18
SVM	0.40	0.50	0.62	0.65

4 DISCUSSION

In terms of computing power, MLC has an advantage in analysing very high spatial resolution imagery.

MLC classification has successfully analysed original 10 cm resolution images, while the SVM has failed to do so. Finally, to create a fair comparison, we decided to reduce and change the spatial resolution of raster datasets and set rules for aggregating or interpolating values across the new pixel size to 0.5.

The Kappa coefficient corrects standardized measures of agreement between two categorical scores produced by the two rates. Based on Landis and Koch measurement of observer agreement The Kappa interpretation of SVM classification gives us an understanding that agreement is substantial for values of 0.57, 0.72, and 0.64 and almost perfect agreement for 0.89. The values for MLC classification have a similar trend of values where classification of images 1-4 have values of 0.54, 0.65, 0.71, and 0.69 respectively. In a comparison of the two classifications, the Kappa coefficient for the MLC classifier shows higher agreement with exception of the last-date image where MLC yields better results.

These results answer the research question, indicating that the SVM classifier is superior and gives better performance in classifying urban classes,, that is refugee settlements in the context of the research.

When it comes to calculating urbanization, the research indicates that there has been an exponential expansion of urban class from 24-12-17 to 24-09-18 from 2.01 km^2 to 5.37 km^2 for SVM. The non-urban class however reduced from 12.58 km^2 to 9.95 km^2. The results found in the research are relevant for urban sprawl analysis in refugee camp settlement and Humanitarian actors.

The evolution and increase in the values of Shannon's Diversity Index indicate that there is an increase in urban sprawl and development tends to be more dispersed over a period of time. This indicates a rapid increase in urban sprawl. The results of this index give us the idea of spatiotemporal patterns of urban growth in Kutupalong Refugee camp.

5 CONCLUSION

We demonstrated the application of remote sensing classification techniques using 4 UAV images from different dates to identify and calculate the urban sprawl in Kutupalong Refugee Camp, Bangladesh which is under great urban expansion due to the influx of Rohingya refugees from neighbouring Myanmar. The Rohingya emergency was one of the biggest crises in 2017, which has severely affected the change of the physical landscape of the host community in Bangladesh.

The research analysed the expansion of the refugee camp from 2017 to 2018. The objective was to understand which of the techniques yielded better results. The research was conducted to understand and evaluate the performance and agreement of two different machine learning classifiers – Support Vector Machine and Maximum Likelihood Classification.

To answer the research question of which machine learning classifier technique yields better performance in urban sprawl classification in Refugee camp context, both of the classifiers' performances were similar in terms of overall accuracy for both of the classes under analysis. In terms of overall accuracy, the advantage has been given to SVM classifier as it produced slightly better results.

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