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Detection and Measure Carstensz Glacier Area Changes Using Machine Learning Technique

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Abstract*: Using satellite data for acquiring glacier outlines has become more popular in the last decade. Glacier change assessment is the main goal for deriving glacier outlines. It's important to make the best method to generate the glacier outline as there most of the glacier outline is made with manual delineation and spectral thresholding. This research used a machine learning model to deriving the glacier pixels from satellite data. The model trained using more than 80 thousand of a glacier and non-glacier pixels. The model that trained has been proved to able classified a glacier pixel with more than 99% accuracy in one of the best experiments. The NDSI (Normalized Difference Snow Index) proved to be the key feature to classifying glaciers and shown to be one the best combination with NDSI + GLCM + TIFF (Band 4). This model hopefully can be further expanded and installed directly in satellite so we can instantly make a glacier outline without any manual delineation or spectral thresholding needed.

***Keywords*: Glacier Area, Image Classification, Machine learning, Remote Sensing.**

I. INTRODUCTION

A glacier is an accumulation of snow, ice, rock, sediment and liquid water that compresses into large, thickened ice masses. A glacier is an indicator of the current climate condition and as an archive for a climate-changing, that occurred [1]. Glaciers in tropical areas can give information about climate change and the small size allowed it to respond to climate change instantly [2].

Puncak Jaya is the highest summit of Mount Jayawijaya (Carstensz Pyramid) with 4884 meters high above the sea level. Puncak Jaya becomes the highest mountain in Indonesia and included in the 7 summits of the world's highest mountain. There are several glaciers at Puncak Jaya including Carstensz, Eastern Northwall Firn, and Western Northwall Firn. This tropical glacier is drastically shrinking and in a short amount of time will vanish [3].

Glacier remote sensing research usually was done at Antarctica and rarely in Indonesia or other tropical areas.

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As one of the wonders of Indonesia, Carstensz glacier lasts researched in 2006 by Klein and Kincaid using 2002 remote sensing data. This makes a huge opportunity to research this glacier as there are not any current area measurements for this glacier.

Remote sensing has been used in many regions of the world such as [4]–[7] with the majority using Landsat data for the last decade. Landsat data is highly available in the Landsat archive at USGS but Landsat satellite has low-resolution images at 30m resolution. This makes the accuracy of classification become lower than using the higher resolution satellite imagery (e.g SPOT data). We used SPOT 6 and 7 satellite imagery with very high resolution at 1,5m per pixel resolution.

Many research used automatic or semi-automatic routines to map the glacier based on the spectral reflectance signature of snow and ice [8]. The spectral reflectance signature was classified by assign a range of thresholds to determine the ice signature. But there is a small number of the experiment using machine learning as their method to generate the glacier outline.

As many of the glacier inventory available online, one of the complete datasets of global glacier outlines was available as The Randolph Glacier Inventory that available via the GLIMS website [9]. This inventory was generated using visual identification or semi-automatic algorithms for the detection of divides in a DEM [6]. These algorithms use standard watershed delineation tools to build a preliminary map of ice 'flow sheds' which are then merged, based on chosen thresholds for the proximity of their termini, to form glaciers.

NDSI is great for detecting snow and ice although, this feature still requires user interaction for the high green band atmospheric scattering and the path radiance [10]. In [11] already compared some feature extraction data and concluded that one of the features data that can support the classification problem is GLCM. Based on that reason, we use the NDSI (Normalised Difference Snow Index) and GLCM (Gray-Level Co-occurrence Matrix) as its features with some experiments on it.

There are 6 combinations of features (NDSI, GLCM, NDSI + GLCM + TIFF (Band4), NDSI + TIFF (Band 1, 2, 3, and 4), NDSI + TIFF (Band 2 and 4), and TIFF (Band 2 and 4). Each of these features will be classified using the SVM, Random Forest, and Decision Tree as these 3 classifiers are the best choices to do the classification as they could produce relatively good accuracy at different scales [12].

SVM can do a good classification for difficult classification problems [13].

Decision Tree algorithm proved to produce high accuracy for various data in remote sensing and produce them with a very fast time [14].

Random Forest used in the last 2 decades and get a lot of interest because of the great classification result and fast in the classification process [15]. RF can handle high dimensionality data and proved to be a fast classifier and insensitive in overfitting [16].

Observation of glaciers using remote sensing is very important because of the difficulty in observing glaciers directly. The location of tropical glaciers that are difficult to reach is a strong reason for research using remote sensing techniques. Glacier surface area can be used as a benchmark for climatic conditions. The smaller the glacier, the hotter the current climate conditions or climate change is happening. In this study, the glacier surface area was calculated using machine learning techniques by classifying glacier pixels from satellite data, then the area was calculated based on the spatial scale of the satellite to get the glacier surface area. The glacier area is presented in a table and graph to illustrate the glacier area changes.

Remote sensing data can be useful for providing information that can be used for classification and much more research. We hopefully can become a reference and make the government aware of the current situation also to provide concrete evidence of the impact of global warming so the thinning of ice in Puncak Jaya can be taken for further action.

II. RELATED WORK

Glacier remote sensing has generated different types of output apart from glacier outline inventory such as ice surface velocity [17]–[19] and mapping glacier mass balance [20], [21]. Much of this research done at mountain glaciers in the non-tropical area and still little research on tropical glaciers especially glaciers at Puncak Jaya.

In [22] using the Landsat TM satellite has been compared to different methods for glacier mapping such as segmentation of ratio images, manual delineation, and unsupervised/ supervised classification. The best result for glacier mapping in the research test area, especially in the regions with cast shadow is the segmentation of ratio image from TM4 / TM5 with raw DN. This makes classification using supervised machine learning more challenging to getting a better result than other methods that exist. Using manual delineation and segmentation of ratio images needs time to do and a specific threshold of spectral reflectance to classified the glacier. Machine learning can be a solution for this kind of problem to generate faster and dynamic spectral reflectances to classifying the glacier.

Some of research has done in Carstensz Glacier including Wollaston (1914), Dozy (1938), Allison (1975), Harrer (1965), Peterson & others (1973), Allison & Kruss (1977), Allison & Peterson (1989), Peterson & Peterson (1994) dan Klein & Kincaid (2006). From all of that, only Allison & Peterson (1989), Peterson & Peterson (1994) dan Klein & Kincaid (2006) used remote sensing. [3] used the IKONOS Satellite to take 2 multispectral images with 3 bands combination. The good result of this research was influenced by the high-resolution image that used.

III. METHODOLOGY

A. Data Gathering

We used SPOT 6 and 7 satellite data. Satellite data was collected from LAPAN (Lembaga Penerbangan dan Antariksa Nasional / National Institute of Aeronautics and Space). https://inderaja-catalog.lapan.go.id/dd4/ is a website that provided the data catalog that used to list all the required data and proposed to LAPAN by a proposal to request the data.

There are 15 data that requested and gathered from LAPAN varies from the year 2013 to 2019. The average of the cloud cover percentages in 15 data is 59.11%. This makes a huge amount of data cant be used cause of cloud cover. Only 4 data that can be used for this research. There are SPOT 6 (2018 October and 2018 December) and SPOT 7 (2015 August and 2019 March).

For validation purposes, this research needs data to validate a classification result. GLIMS (Global Land Ice Measurements from Space) data was used for validating the classification result (pictured in Fig. 1). https://www.glims.org is a website that provides the GLIMS data. We used the SPOT 7 2015 August data to train the machine learning model and the 2015 October GLIMS data to validate the model. GLIMS data used in this research was modified by adjusting the edges into smoother edges by using the node tools in QGIS (pictured in Fig. 2).

Fig. 1. GLIMS Raw Data (October 2015, Carstensz Glacier)

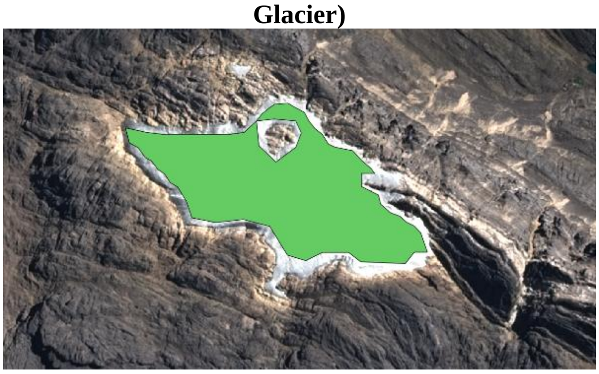

Fig. 2. GLIMS Manual Modified Data.

B. Pre-processing Data

The raw form of data is JP2 file and splits into a various number of data tiles. GDAL (Geospatial Data Abstraction Library) was used to convert tiles of JP2 data into a single TIFF file.

For further process, QGIS was used to finish this research. The TIFF file then clipped to focus on the classification area nearby the Glacier. Using QGIS, the TIFF file clipped by extent (137.173137615, -4.07748417442, 137.193614633, -4.0891969633) for all 4 data. This makes the same resolution of an image for all data with 1474 x 843-pixel resolutions.

TIFF file that generates from the previous step was processed again to improve the data quality by adjusting the band rendering min and max values for each of the 4 data. The 2015 SPOT 7 data used to be the guideline for other datasets. We first set the best min-max value for SPOT 7 2015 data and followed by adjust the other dataset correspond to the min and max value from the 2015 data.

The next step is to extract the feature from the TIFF processed file. GLCM (Grey Level Co-occurrence Matrix) and NDSI were the features used in this research. NDSI was extracted by raster calculator function on QGIS with the equation:

$$NDSI = \frac{Green - NIR}{Green + NIR} \tag{1}$$

The GLCM feature was generated by GRASS r.texture function with SA (Sum Average) textural measurement method. This textural measurement method was based on [23]. Fig. 3 is the TIFF file from SPOT 7 2015 data that used to calculate NDSI data (Fig. 4) and GLCM Data (Fig. 5). This processed was done to all 4 data (2015, 2018-10, 2018-12 and 2019).

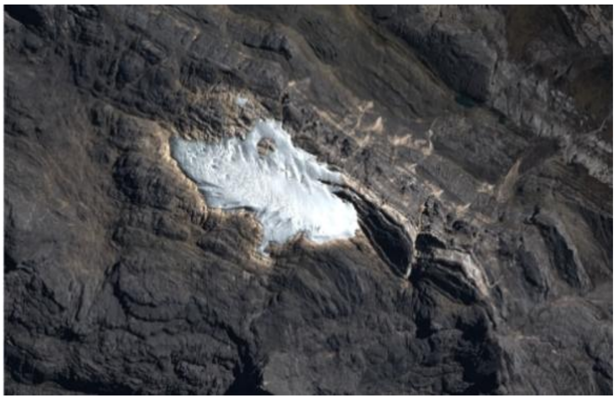

Fig. 3. SPOT 7 2015 TIFF

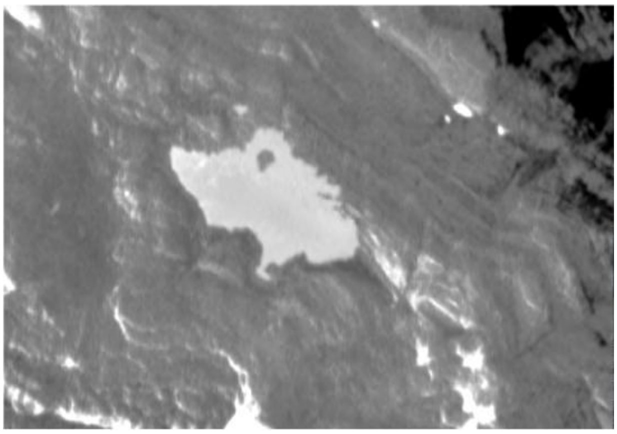

Fig. 4. NDSI 2015

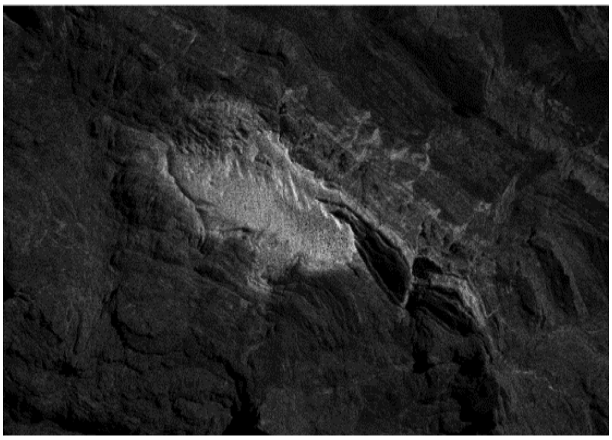

Fig. 5. GLCM 2015

C. Training Model

For Training Model, we used 3 different classification algorithms and some feature mixing experiments. Decision Tree, Random Forester, and Support Vector Machine were used for the classification algorithm. Each data will be divided into 70% of training data and 30% of validation data.

By generating the TIFF, NDSI, and GLCM. We experimented on mixing all the available features. There are:

1. NDSI pictured in Fig. 4
2. GLCM pictured in Fig. 5
3. NDSI + GLCM + TIFF (Band 4) pictured in Fig. 6
4. NDSI + TIFF (Band 2 and 4) pictured in Fig. 7
5. NDSI + TIFF (Band 1, 2, 3 and 4) pictured in Fig. 8
6. TIFF (Band 2, 4) pictured in Fig. 9

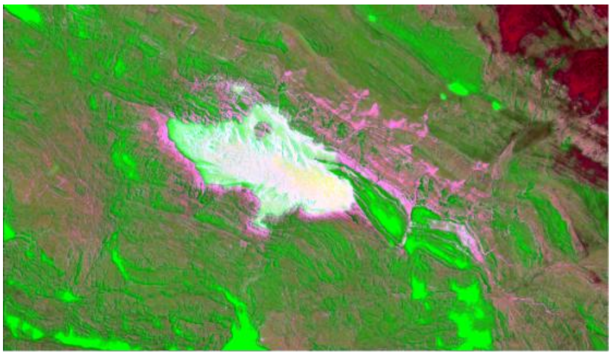

Fig. 6. NDSI + GLCM + TIFF (Band 4)

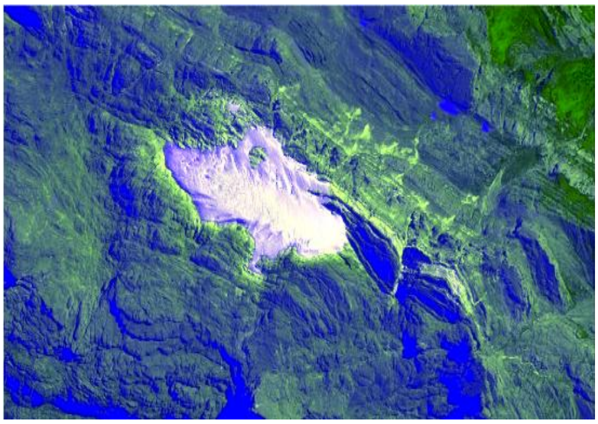

Fig. 7. NDSI + TIFF (Band 2 and 4)

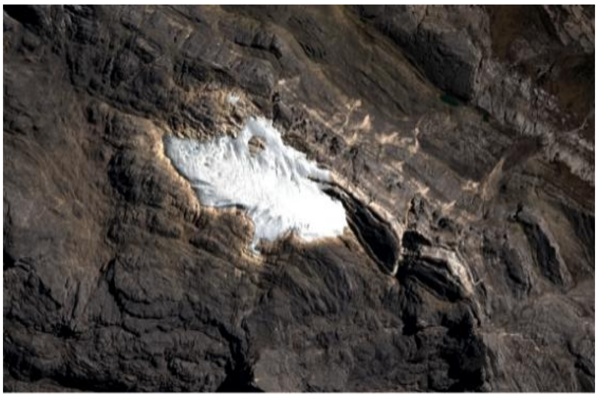

Fig. 8. NDSI + TIFF (Band 1, 2, 3 and 4)

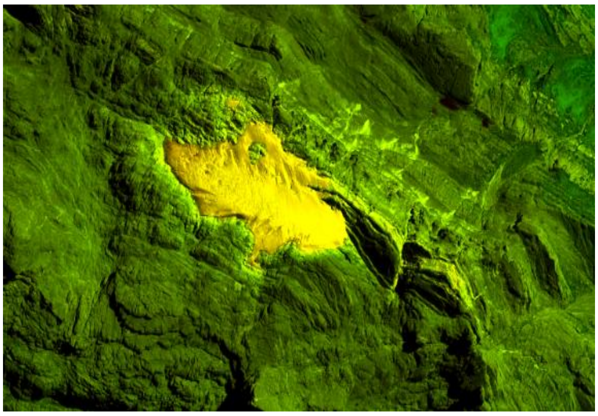

Fig. 9. TIFF (Band 2 and 4)

The image classification model was trained for all 6 features with 3 different classification algorithms. The training was done using OTB (Orfeo Toolbox) plugins from QGIS. OTB needed 3 input files for each train including an input image list for the training, the vector data list for the list of classes and a vector data list for validation (Fig. 10). Data Training and validation in Fig. 10 were created using the GLIMS data as the base to make a polygon of a glacier.

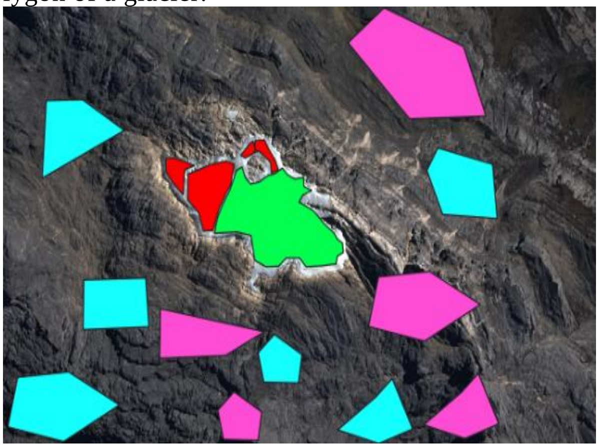

Fig. 10. Data Training (Green: Glacier, Blue: Non-glacier) and Data Validation (Red: Glacier, Pink: Non-Glacier)

By completing this step will generate 2 output: a model and confusion matrix for each training results. There is a total of 18 models created for all features using different classifiers. Each of these will tested using 2015, 2018-10, 2018-12 and 2019 data.

D. Testing Model

The trained model used in this step for classified the glacier and non-glacier class. This step was done using OTB ImageClassifier function. The function needed 2 input files including an image to classify and a model file. This classification process takes a longer time than the training cause of the repetition needed to test each model 4 times (4 variation data).

Fig. 11 and Fig. 12 were examples of classification outputs with 2 class: the blue class is glacier and the other color is a non-glacier. This classification process generates a raster file. With this raster file, a number of each class can be calculated using the Raster layer unique values report. This generates a report for each class including the number of pixels. This number will be multiplied by the resolution of the satellite imagery data and resulted in the actual size of the glacier area. The raster file also needs to convert into a vector to generate the glacier outline. This process was done using QGIS Polygonize tools.

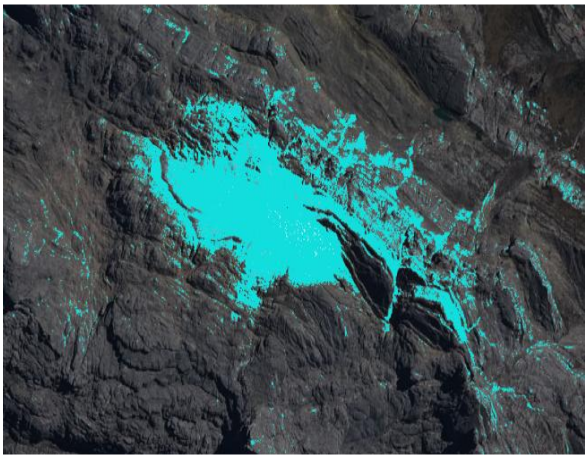

Fig. 11. 2015 GLCM Classify using Random Forester Algorithm

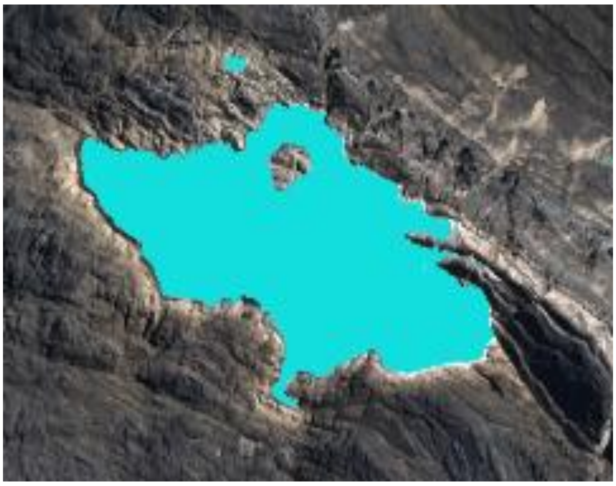

Fig. 12. 2015 NDSI + GLCM + TIFF (Band 4) Classified using Random Forester Algorithm

IV. RESULT AND DISCUSSION

With various features used in this research, the classification result is diverse. All 6 features experimented in this research are tested each using 3 machine learning algorithms. The result is presented in tabular form in Table 1.

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Table 1. Confusion Matrix for all features and algorithms

TIFF (Band 2 and 4)								
Decision Tree			Random Forest			SVM		
	Glacier	Rock		Glacier	Rock		Glacier	Rock
Glacier	13596	1	Glacier	13595	2	Glacier	13597	0
Rock	169	13428	Rock	190	13407	Rock	126	13471
NDSI								
Decision Tree			Random Forest			SVM		
	Glacier	Rock		Glacier	Rock		Glacier	Rock
Glacier	11573	2026	Glacier	11582	2017	Glacier	13599	0
Rock	410	13189	Rock	393	13206	Rock	1874	11725
GLCM								
Decision Tree			Random Forest			SVM		
	Glacier	Rock		Glacier	Rock		Glacier	Rock
Glacier	12908	689	Glacier	12924	673	Glacier	13064	533
Rock	612	12985	Rock	592	13005	Rock	651	12946
NDSI + TIFF (Band 2 and 4)								
Decision Tree			Random Forest			SVM		
	Glacier	Rock		Glacier	Rock		Glacier	Rock
Glacier	13629	0	Glacier	13629	0	Glacier	13629	0
Rock	142	13487	Rock	143	13486	Rock	161	13468
NDSI + TIFF Band (1, 2, 3, and 4)								
Decision Tree			Random Forest			SVM		
	Glacier	Rock		Glacier	Rock		Glacier	Rock
Glacier	13629	0	Glacier	13629	0	Glacier	13629	0
Rock	119	13510	Rock	132	13497	Rock	397	13232
NDSI + TIFF Band 4 + GLCM								
Decision Tree			Random Forest			SVM		
	Glacier	Rock		Glacier	Rock		Glacier	Rock
Glacier	13629	0	Glacier	13629	0	Glacier	13371	258
Rock	14	13615	Rock	3	13626	Rock	470	13159

The confusion matrix describes the best and the worst model according to the validation testing result. From the table, the Support Vector Machine is the best classifier in 3 features (NDSI, GLCM, and TIFF (Band 2, 4)), Decision Tree in 2 Features (NDSI + TIFF (Band 1, 2, 3, 4) and NDSI + TIFF (Band 2, 4)), and Random Forest in 1 feature (NDSI + GLCM + TIFF (Band 4)). The best accuracy reach for this validation is 99.989% for the NDSI + TIFF Band 4 + GLCM using the Random Forest algorithm. From a total of 27.258 of the glacier and non-glacier pixels, only 3 pixels are misclassified.

As pictured in Fig. 13, the Random Forest can classify the glacier really well but still need work on the shadowed part of the mountain. This result proved that NDSI can be used to detect well on a glacier, but still need work on how it differs the glacier with shadow. From this, we experiment on another feature like Bands of TIFF and GLCM.

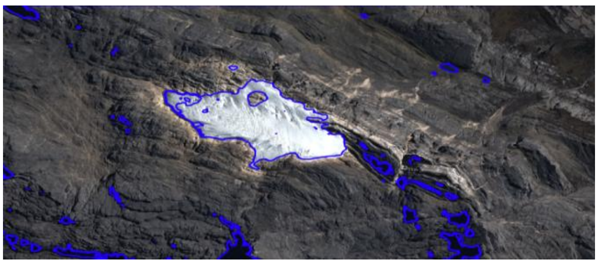

Fig. 13. NDSI 2015 with Random Forest Classifier

Fig. 14 is one of the best results of this experiment. This pictured the perfect glacier outline using the Random Forest Algorithm. Using the mixture of NDSI and Spectral Reflectance from the TIFF file band 2 and 4, the classifier now can difference the shadowed part of the mountain.

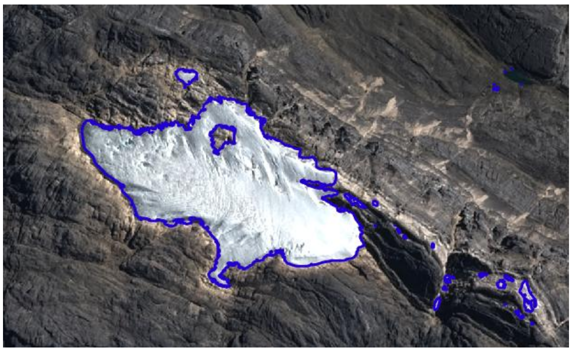

Fig. 14. NDSI + TIFF (Band 2, 4) with Random Forest Classifier

From the various feature that used in this research, NDSI becomes the key feature to classify the glacier as most of the feature that used NDSI has a better result. Nevertheless, the NDSI cannot be used as a single feature. This resulted in the false classification of the shadowed part of the mountain (e.g Fig. 13). The best feature combination for this experiment is the NDSI + TIFF (Band 2, 4) pictured in Fig. 14. Using the combined features (NDSI + TIFF) now the model can differentiate the shadowed part of the mountain and the glacier.

Fig. 15 and Fig. 16 are the outline of the glaciers that generated by the model from the SVM algorithm using NDSI + TIFF (Band 1, 2, 3, 4) feature. This resulted in a bad glacier outline because the model misclassified the non-glacier pixel into a glacier. The model cannot differ the debris cover area well and resulted in a bad glacier outline.

Fig. 15. The Glacier Outline (Blue) Based on the 2015 NDSI + TIFF (Band 1, 2, 3, 4) Using the SVM Classifier.

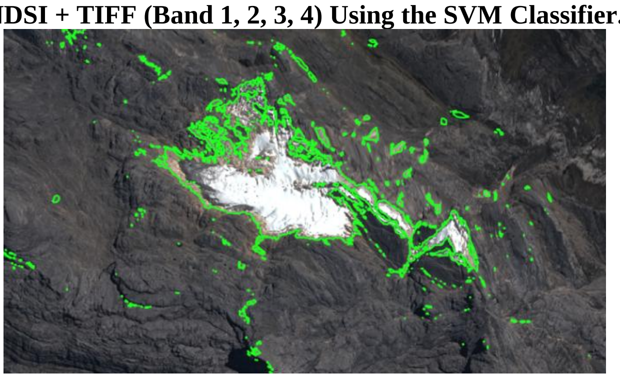

Fig. 16. The Glacier Outline (Blue) Based on the 2018 October NDSI + TIFF (Band 1, 2, 3, 4) Using the SVM Classifier

Fig. 17 shows another problem for the SVM to classify this glacier. Cloud is another problem for the model to correctly classify the glacier outline. The model can easily classify all glaciers, but the model having difficulty in classifying the non-glacier class.

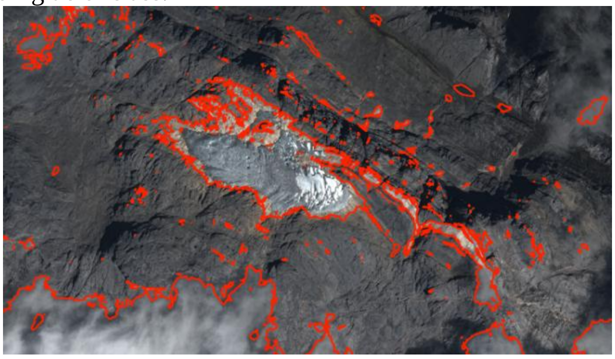

Fig. 17. The glacier outline (Red) base on the 2015 NDSI + TIFF (Band 1, 2, 3, and 4) using the SVM Classification Algorithm.

Fig. 18 illustrated the best classification result for the 2018 December and 2019 data. The NDSI + GLCM + TIFF (Band 4) feature using RF classifiers can easily differ the cloud and make the classification result better than any other feature. In Fig. 18B, the model failed to classify the inner part of the glacier. This caused by the shadowed part of the glacier that has a different spectral reflectance than a normal glacier.

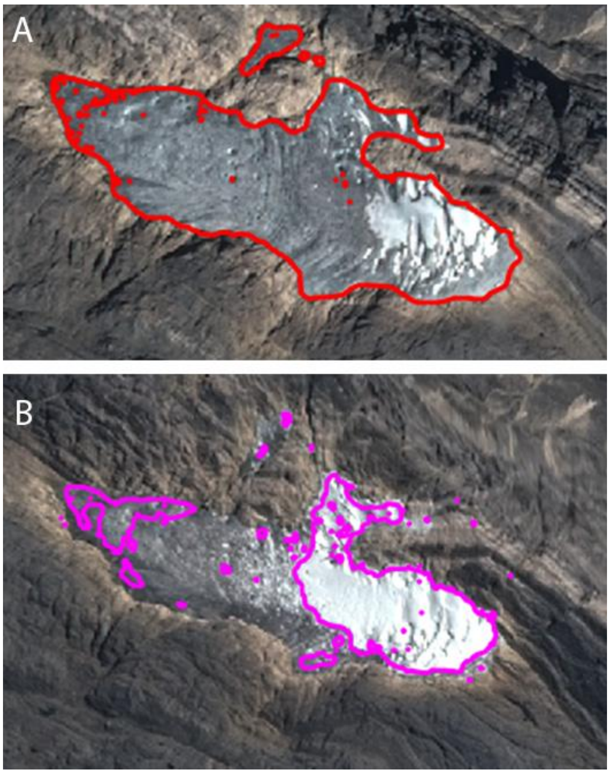

Fig. 18. NDSI + GLCM + TIFF (Band 4) Based on 2018 December Data (A) and 2019 Data (B) Using the RF Classifier

As mentioned in the previous section, this study will only calculate accuracy using the 2015 data because the availability of verification data is limited only for 2015 using the GLIMS data. There are around 40.379 pixels of a glacier used to training data and 26.782 pixels glacier used to validation with a 70: 30 training and validation ratio.

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From all the classification results, we record all the glacier pixels and calculate the glacier area from the number of glacier pixels.

Table 2 is the final result of the classification and presented the number of glacier pixels and the final glacier area after calculated. The glacier area was calculated using the multiplication of the number of pixels and satellite spatial scale as mentioned in chapter 3. As seen in the table, 2018 October to 2018 December has an increment in 5 features. The only decreasing result is the NDSI + GLCM + TIFF (Band 4) using the RF classifier. Otherwise, this only decreasing result is the best feature as the other 5 features failed to classified non-glacier class correctly and cause a misclassification for the cloud into glacier class. Based on the table, we generate a graph to more descriptive the glacier area size.

Table 2. Table of Amount of Glacier Pixel and Glacier Area Result

	Number of Glacier Pixel					
	NDSIB24 - RF	NDSIB4GLCM - RF	NDSIB1234 - DT	B24 - SVM	NDSI - RF	GLCM - RF
2015-8	71,859	65,767	71,317	71,536	152,053	152,053
2018-10	69,234	54,635	66,225	69,478	128,385	128,385
2018-12	114,321	43,662	104,553	111,194	133,572	133,572
2019-3	56,220	17,587	42,130	43,155	114,241	114,241
	Glacier Area (m^2)					
	NDSIB24 - RF	NDSIB4GLCM - RF	NDSIB1234 - DT	B24 - SVM	NDSI - RF	GLCM - RF
2015-8	161,683	147,976	160,463	160,956	342,119	342,119
2018-10	155,777	122,929	149,006	156,326	288,866	288,866
2018-12	257,222	98,240	235,244	250,187	300,537	300,537
2019-3	126,495	39,571	94,793	97,099	257,042	257,042

As pictured in Fig. 19, the orange line represents the best glacier classification result. The graphs show the constant decreasing in the glacier area and getting worse. From the graph can be seen that GLCM with RF classifier is way above the other features. GLCM failed to classify the non-glacier class and resulted in a large amount of non-glacier class to misclassified into glacier class. This makes the number of glacier pixels and the glacier area increase.

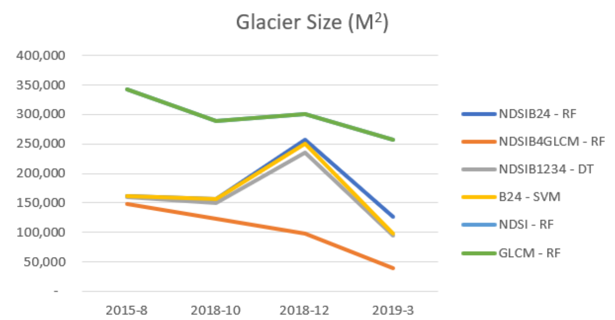

Fig. 19. Glacier Graph Trends from 2015 to 2019 Data

V. CONCLUSION

This research has presented a new method to determine and calculated the glacier outline and glacier are based on the machine learning supervised algorithm. This method accurate up to 99% of training accuracy. As many features combined and experimented in this research, NDSI proved to be the key feature to classify the glacier. NDSI can perform very good using combinations like TIFF (Band 2, 4), TIFF (Band 1, 2, 3, and 4) and GLCM + TIFF (Band 4). As few classifiers are compared in this research, the Decision Tree and Random Forest generate the best result.

This research can be better with much more training data and validation data. With the glacier getting thinner, the need for higher resolution satellite imagery will be increased. Machine learning performs really well in classifying clear glacier area with the right feature and right supervised algorithm.

This model could be implemented in the satellite directly and hopefully can be calculated and detecting glaciers with more efficient and faster time. Within this research, hopefully, people and the government will realize how critical climate conditions in the world currently and make people understand global warming is really happing and it's getting worse.

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