COMPARISON OF MAXIMUM LIKELIHOOD AND SUPPORT VECTOR MACHINE CLASSIFIERS FOR LAND USE/LAND COVER MAPPING USING MULTITEMPORAL IMAGERY

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ABSTRACT

Most of the previous research was related to non-parametric classification methods, states that the Maximum Likelihood (ML) and Support Vector Machine (SVM) methods are the leading classification methods in producing high accuracy. However, only a small proportion of studies have compared the performance of these two methods using multitemporal remote sensing imagery, particularly on Sentinel-2 and Landsat data. This study tries to test and compare the performance of ML and SVM classifiers to mapping land use/cover using Sentinel-2 and Landsat multitemporal imagery data. The Tabunio watershed with an area of 62,586 ha has been mapped with ten types of cover and land use. All classification results show a high overall accuracy (OA) ranging from 86% to 95%. Among the two classifiers, 4 data series with different images and sample sizes, SVM produced the highest OA than ML.

Keywords: *Sentinel-2; Landsat, Maximum Likelihood (ML); Support Vector Machine (SVM);*

INTRODUCTION

Land use/cover maps are currently very important and indispensable in various fields, especially for monitoring and management of natural resources, development strategies, and global change studies (Auliana et al., 2018; S. Kadir et al., 2013, 2016; Z. Abidin, 2019). The land use/cover map is one of the most important documents providing information for various applications, such as monitoring land use, environmental services, urban planning, natural resource conservation, agricultural monitoring, and land use/cover change dynamics (Abbas & Jaber, 2020; Gebhardt et al., 2014; Gómez et al., 2016; Guidici & Clark, 2017; Nurlina et al., 2020; Yunus et al., 2018).

Multiresolution remote sensing satellite imagery data as one of the most important data sources for land cover mapping (Topaloğlu et al., 2016) apart from its wide geographical coverage and efficient cost, it also provides information from semi-detailed to very detailed scale which makes Remote Sensing data irreplaceable (Khatami et al., 2016). Land use/cover maps are usually made based on the approach of several remote sensing image classification methods (Chen et al., 2017; Duro et al., 2012; Imran & He, 2015). However, accuracy and processing time are still challenges for the remote sensing community (Gómez et al., 2016).

Sentinel-2 with the latest generation of earth observation missions from ESA (European Space Agency) designed for land and coastal applications, including the Sentinel-2 A and Sentinel-2 B satellites launched in June 2015 and March 2017, respectively (Thanh Noi & Kappas, 2017). Sentinel-2 remains active and enhances the mission of Landsat and SPOT (Systeme Probatoire d'Observation de la Terre) (Wang et al., 2017). Sentinel-2 has wide

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coverage capability, high spatial resolution (10–60 m), and temporal resolution (ten days for Sentinel-2 A, B / five days Sentinel-2 A + B), and includes multispectral satellite imagery (13 spectral channels). Sentinel-2 has also received major research attention because of its free access and global coverage. Various applications have been applied with Sentinel-2 A, particularly in land use and land cover mapping, the practicality and effectiveness of Sentinel-2 have been tested and show high application potential (Gao et al., 2017; Yang et al., 2017). However, because this is a new type of satellite image, so there is still little research using Sentinel-2 for land use/cover mapping, more research is needed to conduct and evaluate the usefulness of this satellite imagery. Before Sentinel-2 One of the most important and most widely used digital data for remote sensing work is the Landsat satellite. Landsat satellite missions have continued to collect global imagery since 1972 and monitor the Earth biweekly with a resolution of 30 m x 30 m. Landsat's open access policy in 2008 allowed researchers to access this data freely so that monitoring of previously impossible land cover changes was very easy to implement (Eitel et al., 2011).

Landsat data is also not static either, these satellite data products have evolved rapidly over time, providing more data for researchers, and allowing more accurate classification of different and more advanced processes. Landsat 5-TM (8 bits radiometric) has seven channels, and Landsat 7- ETM+ (9 bits radiometric) has eight spectral bands with a resolution of 30 m. whereas, the latest generation Landsat 8-OLI has 11 bands (12 bit radiometric), and this technology is considered the best choice for environmental analysis (Clevers et al., 2017; Sibanda et al., 2015). Classification using Landsat imagery is not only cost-effective but also accurate for making land cover maps that can be used for environmental management, urban planning, forestry, agriculture, and many other sectors.

According to Lu and Weng (Lu & Weng, 2007), not only image suitability but also the determination of the appropriate classification method can affect the accuracy of land use/cover mapping. Several kinds of literatures with various classification methods have been developed and tested for land use/cover mapping from remote sensing data (Brodley & Friedl, 1997; Li et al., 2014; Waske & Braun, 2009). This method uses a supervised parametric algorithm classifier, namely Maximum Likelihood (ML) and the Support Vector Machine (SVM) algorithm. In recent years, nonparametric methods (machine learning-based algorithms) have become a major concern of remote sensing based applications. The use of the SVM and ML classification algorithms has significantly increased. Most of the studies used the ML method as one of the criteria for comparison with other machine learning algorithms (Basukala et al., 2017; Jhonnerie et al., 2015; Khatami et al., 2016).

Several studies have been conducted to determine the best classification method for land use /cover mapping trying to compare the accuracy of these classifiers with either the same method or with different classification methods. However, the conclusions are quite mixed. Additionally, to the best of our knowledge, only a small number of published studies have compared and evaluated the time series performance of SVM and ML against different satellite imagery, particularly in Indonesia. Therefore, this study compares and evaluates the performance of ML and SVM for land use/cover mapping in the Tabunio watershed of South Kalimantan using multi-spatial-temporal satellite data from Sentinel-2 and Landsat data. The purpose of this study was to evaluate the performance of the two best classifiers, namely ML and SVM on Sentinel-2 imagery and Landsat data series.

In addition, to the best of our knowledge, only a limited amount of research was published that compared and evaluated the performance of SVM and ML in time series with different satellite imagery, especially in Indonesia. Therefore, it is practical for a study to compare and evaluate the performance of ML and SVM for land use/cover mapping in Tabunio

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Watershed South Borneo using multi spatial temporal satellite data, Sentinel-2, and Landsat series. The objective of this study is to evaluate the performance of the two most increasing classifiers, ML and SVM when applied to a Sentinel-2 image and Landsat Series.

MATERIALS AND METHODS

Materials used in this study include a 1: 50,000 scale digital map of the Indonesian Earth Administration (RBI), as a reference for administrative boundaries at the research location. Obtained from the Geospatial Information Agency (BIG). Landsat TM/ETM+ /OLI 8 OLI TIRS Satellite Imagery 2005, 2010, 2015, 2020 which is multispectral data with a spatial resolution of 30 m downloaded from http://earthexplorer.usgs.gov/ path 117 row 62. Sentinel-2 the year 2020 Satellite Imagery which can be accessed through the website https://sentinel.esa.int/web/sentinel/sentinel-data-access. The details of the Landsat images used for this study are provided in Table 1.

Table 1. Satellite images used in this study

Year	2005	2010	2015	2020
Months	15-October	20-November	18-November	12- September
Sensor	Landsat TM	Landsat TM	Landsat OLI	Sentinel 2

STUDY AREA

The research location is in the Tabunio Watershed (DAS) which is located in Tanah Laut Regency with an area of 62,558.56 ha which is geographically located at 3 ° 37'2.72 "-3 ° 51 '51.43" LS and 114 ° 36'12.02 "-114 ° 57'47.62" East Longitude. The Tabunio watershed from upstream to downstream is a rural, urban, and coastal area with a distinctive heterogeneous land cover, covering ten land cover classes, namely: settlements, plantations, rice fields, bare land, mining, forest, swamps, shrubs, ponds, and water bodies. The Tabunio watershed consists of 44 villages administratively, 4 sub-districts, and 10 sub-watersheds (ecologically). The map of the Tabunio watershed research location is shown in Figure 1.

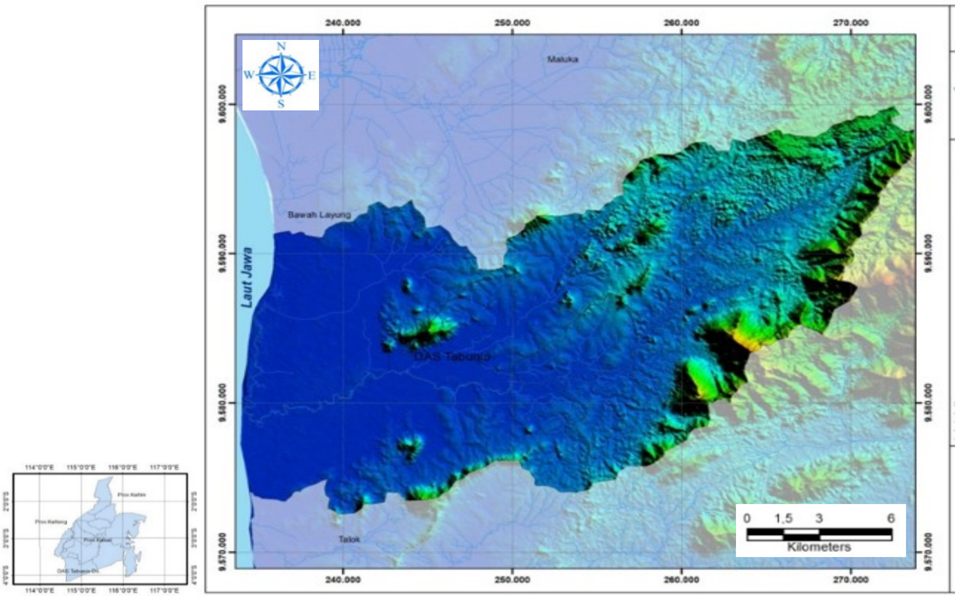

Figure 1. Location of the study area in Tabunio Watershed

TRAINING AND TESTING SAMPLE DATASETS

Training data (training and test samples) is drawn based on manual interpretation of the Sentinel-2 and Landsat data series and available high-resolution imagery from Google Earth.

To collect training sample data, the polygon generates tool in the ArcGIS 10.5 toolbox is used to create polygons for each land cover class. Due to the different polygon sizes, the number of pixels for each land cover class is also different (Table 2).

We took ten land cover categories, namely: water body, forest, bare land, residential, plantations, agriculture, swamps, shrubs, pond, mining. A total of 86,345 sample points were used for training and then tested for accuracy assessment. Training samples are often used for accuracy assessments (Jensen, 1996; Sexton et al., 2013; Sloan & Pelletier, 2012). The accuracy classifications were observed based on field survey data and high-resolution satellite imagery from Google Earth that was taken randomly for each land cover class. Furthermore, overall accuracy (OA), user accuracy (UA), and manufacturer accuracy (PA) are calculated and tested using the confusion matrix and Kappa coefficients.

Table 2. Training and testing sample sizes were used in this study.

Land Cover	Training sample (pixels)				Testing sample (pixels)			
	2005	2010	2015	2020	2005	2010	2015	2020
Water body	354	450	348	403.335	406	124	86	159.505
Forest	259	56.082	17.044	8.996.502	314	38.261	5.121	2.455.313
Bare land	21.804	19.716	4.643	6.723.879	22.193	10.246	890	4.258.246
Residential	1.142	4.882	3.152	2.136.693	1.188	1.903	351	1.083.735
Plantation	893	31.736	37.881	19.184.554	937	14.380	7.776	9.444.056
Agriculture	1.351	1.314	876	4.154.898	1.596	713	200	1.308.608
Swamp	16.741	334	370	148.135	17.183	145	66	16.405
Shrubs	204	251	532	133.906	251	88	134	50.072
Pond	166	330	73	43.405	322	194	18	45.559
Mining	724	3.159	2.182	330.744	738	2.565	279	172.107

Major transformations include an increase in housing and plantations and a sharp decline in forests and shrubs. residential coverage in the study area increased by 1,382.18 hectares, (from 619.07 hectares in 2005 to 2,001.24 hectares in 2020) with an increase of 223.27%, while plantations increased by 23,811.15 hectares, (from 502, 16 hectares) in 2005 to 24,313.31 hectares in 2020) with an increase of 474.2%, while forests decreased by 3,056.79 hectares (from 16,223.67 hectares to 13,166.88 hectares) while shrubs decreased by 9,630, 20 hectares (from 10,846.53 acres to 1,216.33 acres) from 2005 to 2020. The historical changes in land cover in the study area during 2005-2020 are shown in Table 3 and Table 4 and Figures 4a-d.

Table 3. Land Use/Land Cover Data in Tabunio Watershed 2005 – 2020

Land Use/Land Cover	Tahun			
	2005 (acres)	2010 (acres)	2015 (acres)	2020 (acres)
Water body	592,64	386,64	368,50	406,48
Forest	16.223,67	14.004,85	14.699,89	13.166,88
Bare land	3.712,99	4.945,80	13.247,55	7.906,35
Residential	619,07	991,83	1.451,73	2.001,24
Plantation	502,16	7.710,81	20.866,44	24.313,31
Agriculture	21.021,27	10.313,42	8.366,95	12.917,27
Swamp	6.759,52	3.818,56	161,37	181,88
Shrubs	10.846,53	17.042,34	1.695,94	1.216,33
Pond	45,88	126,24	47,96	36,14
Mining	2.172,66	3.155,88	1.590,04	350,50

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Table 4. Land use/land cover change between 2005 and 2020

Land Use/Land Cover	2005–2010 (acres)	2010–2015 (acres)	2015–2020 (acres)	2005–2020 (acres)
Water body	-206,00	-18,14	37,98	-186,16
Forest	-2.218,82	695,04	-1.533,01	-3.056,79
Bare land	1.232,82	8.301,75	-5.341,20	4.193,36
Residential	372,77	459,90	549,51	1.382,18
Plantation	7.208,65	13.155,63	3.446,87	23.811,15
Agriculture	-10.707,86	-1.946,46	4.550,32	-8.104,00
Swamp	-2.940,96	-3.657,19	20,50	-6.577,65
Shrubs	6.195,82	-15.346,40	-479,62	-9.630,20
Pond	80,37	-78,28	-11,82	-9,73
Mining	983,22	-1.565,85	-1.239,54	-1.822,17

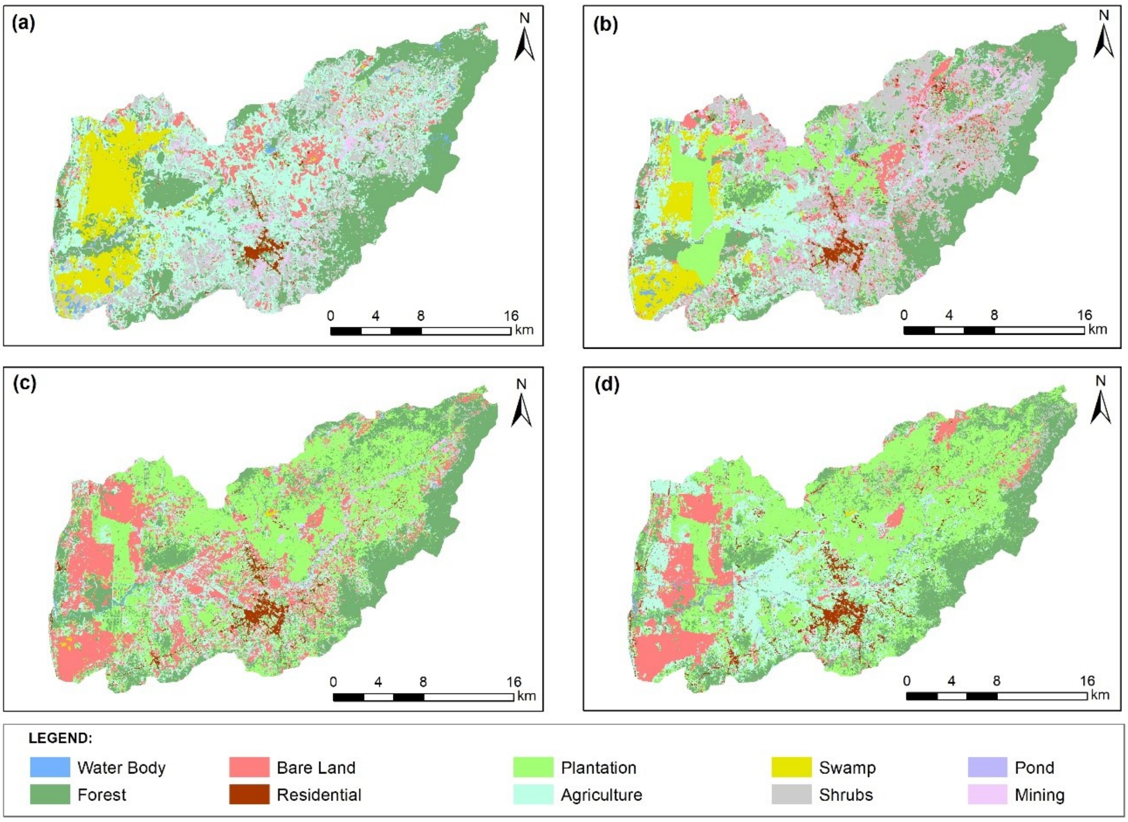

Figure 2. Land cover map classified based on SVM approach a 2005; b 2010; c 2015; d 2020

TM is Thematic Mapper, ETM+ is Enhanced Thematic Mapper, and OLI is Operational Land Imager. The maximum likelihood classification is calculated using the following discriminant functions for each pixel.

$$g_i\,(x) - \ln p\,(\omega_i) - \frac{1}{2}\ln|\Sigma_i| - \frac{1}{2}(x - m_i)^i \sum\nolimits_i^{-1}(x - m_i)$$

where i = class, x = n-dimensional data (where n is the number of bands), $p(\omega_i)$ = probability that class ω_i occurs in the image and is assumed same for all classes, $|\sum_i|$- determinant of the covariance matrix of the data in a class, $\sum_i^{-1}$ = its inverse matrix, m_i= mean vector of a class.

SVM algorithm finds a hyperplane to separate the database based on a pre-defined number of categories (Mountrakis et al., 2011). SVMs approach is generally organized into four

Kernel functions: linear, polynomial, radial basis function (RBF), and sigmoid (Kavzoglu & Colkesen, 2009; Lee et al., 2017). RBFs are more powerful kernels than others (linear, polynomial, radial) and are used to achieve better results (Rimal et al., 2020). The following are the equation of each Kernel functions used in SVM:

$$(i)\ Linear: K\ (x_i, y_i) = x_i^T . x_j$$

$$(ii)\ Polynomial: K\ (x_i, y_i) = (g\ . x_i^T . x_j + r)^d,\ g > 0$$

$$(iii)\ Radial\ basis\ function: K\ (x_i, y_i) = e^{-g(x_i - x_j)^2}, \qquad g > 0$$

$$(iv)\ Sigmoid: K\ (x_i, y_i) = \tan h\,(g\ . x_i^T . x_j + r)$$

where g, d and, r are user-controlled parameters of kernel function

ACCURACY ASSESSMENT AND COMPARISONS

In order to assess classification accuracy, there are many methods available in the literature. The confusion matrix and the Kappa coefficient are among the most popular. For several decades, the Kappa coefficient has been rarely used in assessing the classification accuracy of remote sensing data (Heydari & Mountrakis, 2018). One of the drawbacks of OA metrics is the lack of performance classes that are specific to them. He and Garcia (Gautheron et al., 2019) stated that if the input data (training sample) is not balanced, then the OA value could be wrong because the last class will be classified very poorly. He and Garcia (Gautheron et al., 2019) also suggest that when choosing OA as the criterion metric, the class distribution should be followed by those that occur naturally.

In this study, we used a stratified sampling approach; This approach fits well with OA metrics. In addition, to compare the accuracy of each classification method, we used the same training (input) and testing (validation) dataset; thus, the effect of individual class distributions on OA does not bias the results. We also calculated the 95% confidence interval (error tolerance) δ of the probability estimates (Baraldi et al., 2006) for each OA. Since we used the same test dataset for all classification accuracy assessments, δ did not differ significantly. Therefore, to assess and compare the performance of different classifiers and data sets, we used overall accuracy (OA) as the criterion.

In this study, the overall accuracy of the LULC classification achieved by using the SVM classifier is 96.79% (2005), 92.7458% (2010), 90.93% (2015), and 86.20% (2020). The overall classification accuracy of the alternative ML classifier is 94.79% (2005), 88.64% (2010), 85.38% (2015), and 64.20% (2020). The SVM classifier received a higher OA than the ML classifier across all classification years. SVM obtains a maximum accuracy of 96.79% and a minimum of 86.20%, while the ML classification ranges from a minimum of 64.20% in 2020 to a maximum of 94.79% in 2005. The average overall accuracy of SVM is 91.66% and ML 83.25%. The difference in OA between the two classifications shows that SVM has a better accuracy of 10.8% compared to ML in determining the type of land cover.

The SVM classifier identifies all classes more accurately than the ML classifier (Figures 4, 5). For example, during 2005, the highest UA SVM in terms of Forest (99.56%) was seen, while the ML classification for that year was relatively lower (60.5%). Likewise, the highest SVM related to mining, swamps, deforested land, settlement were 98%, 97%, 96.5%, 95%, and 94.5% respectively during 2005, 2010, 2015, and 2020. In contrast, ML classifier for each class in the same year is as follows: 60.5%, 98%, 81%, and 87.56%.

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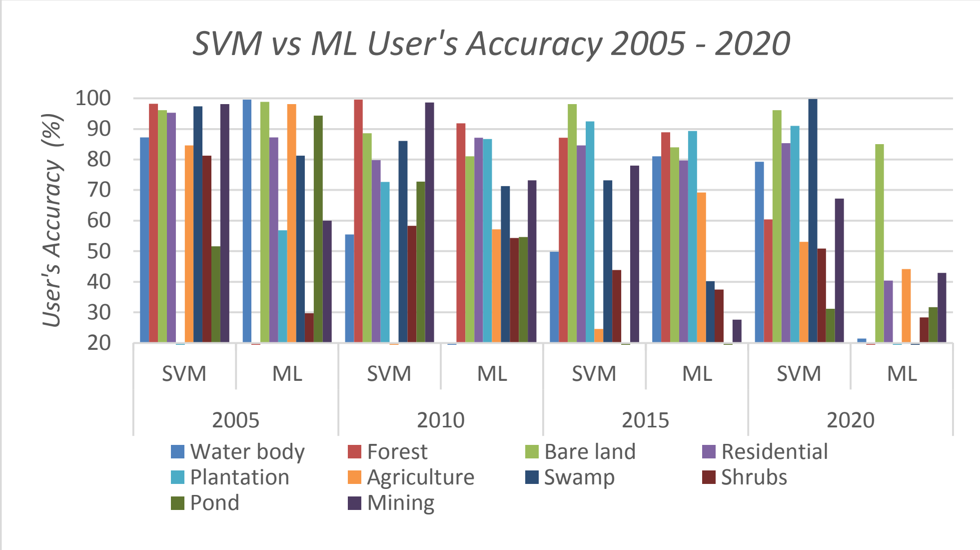

Figure 3. User's accuracy assessment

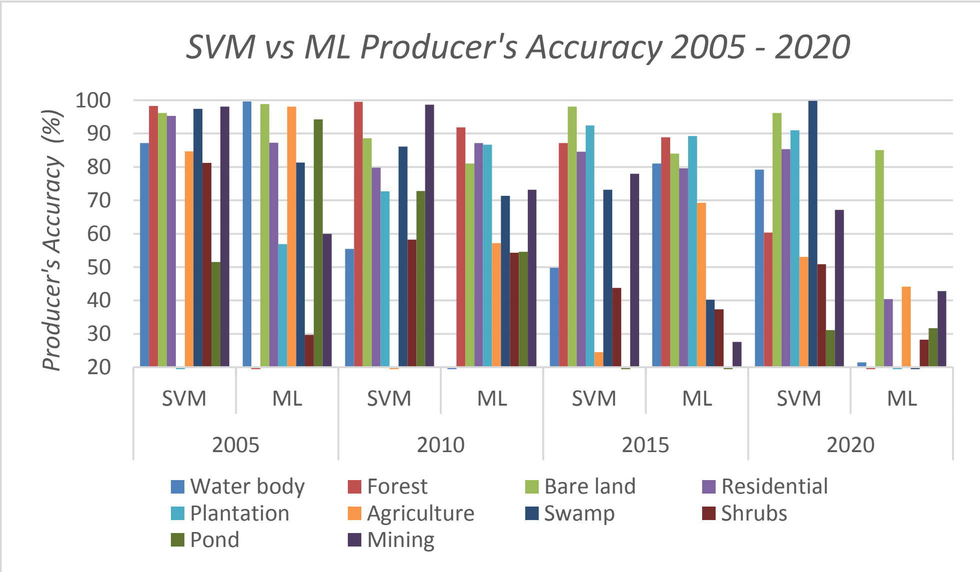

Figure 4. Producer's accuracy assessment

Producer accuracy (PA) of the SVM classifier is also relatively higher than the highest ML.PA classifier for SVM it was 99.98% for swamps in 2020, while ML was 92.45% for agriculture. PA ponds were found 83.0% in 2015, and forests remained the highest (96.56%) in 2016. Again, 2020 was found to be important for Bare land (98.1%), whereas PA SVM was found to be consistently dominant in 2005, 2015, and 2020. On the other hand, ML was found to be 99.64% in 2005 and bare land was found to be 98.87% in 2005. The ML classification of sand areas for 2013 was 86.67%, and that the water body for 2015 was 94.18 %. The PA yields for ML shrubs observed in 2005, 2010, and 2015 were 81.27%, 97.77%, and 94.65%. The highest UA and PA from SVM classifiers were most seen in the bare land (Figs. 4 and 5), and the lowest UA from SVM was observed in housing (84% during 2005) and the lowest PA SVM in Pond (75.56%) during 2005) in Table 5.

Table 5. Producer's Accuracy dan User's Accuracy between SVM and ML

Land Use/Land cover	2005		2010		2015		2020	
	SVM	ML	SVM	ML	SVM	ML	SVM	ML
(a) User's Accuracy								
Water body	87,19	99,64	55,46	0,92	49,77	81,03	79,24	21,44
Forest	98,25		99,56	91,84	87,17	88,9	60,39	0
Bare land	96,13	98,87	88,57	81,08	98,1	83,97	96,15	85,02
Residential	95,3	87,24	79,78	87,17	84,6	79,65	85,37	40,39
Plantation		56,86	72,68	86,68	92,45	89,32	90,96	0
Agriculture	84,65	98,1	8,75	57,14	24,55	69,21	53,06	44,16
Swamp	97,43	81,29	86,08	71,34	73,19	40,22	99,77	3,61
Shrubs	81,27	29,72	58,27	54,28	43,82	37,4	50,9	28,3
Pond	51,55	94,3	72,77	54,59	8,55	14,68	31,12	31,72
Mining	98,10	60	98,63	73,15	78	27,63	67,17	42,85
(b) Producer's Accuracy								
Water body	87,84	94,52	91,08	16,49	86,36	42,18	74,95	53,73
Forest	96,72	95,25	93,67	86,34	96,56	86,16	83,41	0
Bare land	98,28	97,76	93,51	9,05	95,92	78,16	66,19	72,43
Residential	92,92	94	94,46	62,01	73,15	55,2	85,17	66,31
Plantation		87,09	94,74	85,21	96,01	83,83	74,56	0
Agriculture	79,8	93,67	1,38	86,08	46,01	54,32	87,54	92,45
Swamp	99,36	91,7	59,02	25	81,58	50,71	99,98	44,44
Shrubs	70,59	91,36	52,59	74,54	46,85	77,75	53,72	86,44
Pond	83	98,51	79,89	79,2	11,16	86,43	23,33	23,1
Mining	98,5	94,52	60,83	69,06	29,17	69,86	80,9	71,41

SVM = Support Vecor Machine, ML = Maximum Likelihood

DISCUSSION

SVM and ML are well-known methods for assessing the accuracy of land cover classification in any area (Bray & Han, 2004; Srivastava et al., 2012). ML is a classical parametric classification method used assuming multivariate normally distributed data (Kavzoglu & Colkesen, 2009). In particular, SVM yields better accurate land cover classification due to its nonparametric nature (Rimal et al., 2020; Thanh Noi & Kappas, 2017; Vapnik & Chervonenkis, 2015). SVM reduces the misclassification of land cover from hidden information or controls the level of certain misclassifications. SVM and ML are very popular in land cover classification because they have higher accuracy compared to other algorithms in identifying land cover classes in watersheds and others (Bray & Han, 2004; Huang et al., 2002; Kavzoglu & Colkesen, 2009; Schneider, 2012). However, (Campbell, 1981; Hixson et al., 1980; Scholz et al., 1979) argued that the selection of sample data (training data) is more important than the selection of a classification algorithm to achieve a higher classification accuracy of the classified images. Accuracy assessment is an important stage and must be carried out in the classification and mapping of land cover (Lin, 2013). Accuracy assessment refers to the analysis process carried out to show the level of truth of a map or classification results (Foody, 2002). Accuracy assessments are carried out to assess map quality, evaluate various classification algorithms and identify errors. The assessment and validation of land cover maps provide a measure of data quality including overall accuracy, user accuracy, and producer accuracy. In an assessment, high accuracy means that misclassification of land

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cover is low. Producer accuracy states how well a certain area can be classified, and user accuracy ensures that the pixels classified in the image exactly match the category in the field (Congalton, 1991). Accuracy assessment is fundamental but challenging in the thematic mapping (Foody, 2002).

CONCLUSIONS

Higher user and producer accuracy are obtained from the SVM classification method compared to the ML classifier. SVM has proven to be effective in determining land cover classification, especially on open land. This is associated with higher accuracy ratings due to different signatures; However, the different signatures of open land also result in a higher accuracy of the ML classification method. Of the ten total land cover classes, the highest accuracy of users and producers is seen in open land, while the accuracy of users and producers in pond classes is lower. Based on the evidence obtained from our study, we recommend SVM as a suitable option for proper land use / land cover classification, particularly in heterogeneous areas such as riverbed blood.

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