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Multi-temporal Land-Cover Classification of Kinabalu Eco-Linc Site and the Protected Park Areas

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Multi-temporal Land-Cover Classification of Kinabalu Eco-Linc Site and the Protected Park Areas

C F Miuse* and K U Kamlun
Faculty of Science and Natural Resources (Forestry Complex), Universiti Malaysia, UMS Road, 88400 Kota Kinabalu, Sabah, Malaysia

Email: charmilafloramiuse@gmail.com

Abstract. The Crocker Range Park and Kinabalu Park are Sabah's largest terrestrial parks physically separated by approximately 10 km. Both parks are involved in a set up plan of ecological linkages to connect and further strengthen the biodiversity conservation efforts in the State of Sabah. The part of ecological linkages project is known as Kinabalu Eco-Linc (Kinabalu Ecological Linkage). This study is designed to monitor the land use change of the area between year 1991 - 2018 using Landsat imagery. Maximum likelihood classifier was used to create the land cover change map of both protected areas. Seven land cover type were identified in the area which comprises of primary forest, secondary forest, shrubland/grassland, barren land, agriculture, plantation, and river. The result illustrated a drastic declined of primary forest and increased secondary forest and agricultural over the period of 28-years assessed. The spatial changes that occur throughout the period within state park and KEL area is drives by natural and anthropogenic activities. To support the increase in local population and their demand, the natural environment underwent changes for their welfare improvement. It is concluded that, monitoring protected area using remote sensing technique provide useful spatiotemporal data to locate key areas that are vulnerable to threat and can be utilized for better management of both protected areas and human use resources in adjacent area.

Keywords: Land cover change, Deforestation, REDD+, Supervised classification

1. Introduction

Deforestation is a major global concern that continuously induces a wide range of detrimental impact to many countries. FAO (2010) defined deforestation as transformation from forested land to non-forested land during a certain time. Notable investigations and studies have been conducted to cater this issue particularly on the drivers of deforestation [1-2]. These studies add crucial understanding in facilitating the development of policy and management plan for estimating the decline rate of deforestation in regional, national, and global scale. In Sabah, Malaysia, the rate of deforestation demonstrates an estimation of 1.6 % per year between 1990 and 2008 for all forest types and it is predominantly driven by extensive land use and land cover change [3]. This indicates that continuous conversion of forest to non-forest without proper control of immense land use planning to sustain the natural ecosystem may lead to serious deforestation to the tropical rainforest in Sabah.

Dramatic change of land use and land cover often associated with the economic development and social progress especially in developing countries. For example, growth in human population increases the demand for provisioning services such as food, clean water and wide range of for ecosystem services that contribute to their well-being. This has increased the needs for more anthropogenic activities such as land conversion from forested land to agricultural land to support their needs for livelihood. This eventually leads to negative substantial cost on the environment and ecosystem function of the natural forest. Increase in commercials production of agricultural product such as rubber and palm oil have replaced substantial areas of natural forest. In Malaysia, oil-palm plantations show a substantial expansion from 2.4 million to 5.8 million hectares within 28 years from 1990 to 2018 [4]. Hence, rapid land conversion for the purpose of high opportunity cost such as commercial agriculture may lead to forest lost, this eventually instigating the only remaining forest cover to be in gazetted forest areas such as forest reserve and parks [3].

In effort to reduce forest conversion and lowering the carbon emission, Sabah's Reducing Emissions from Deforestation and Degradation (REDD+) readiness is enhance by introducing a programme called "Tackling Climate Change through Sustainable Forest Management and Community Development". This programme is co-finance by the Sabah State Government and the European Union (EU). This project has been implemented in three selected pilot sites across all areas in Sabah. These include Kampung Gana, Kota Marudu, Kinabatangan, and Kinabalu Eco-Linc (KEL). Particularly in KEL area, Sabah Park and various stakeholder participated in activities such as restoring degraded habitat by the local community, educating program on sustainable agriculture and land management as well as providing opportunity for community tourism in that area [5].

This study aims to generate multi-temporal land cover classification and changes in Kinabalu Park, Crocker Range Park and the Kinabalu Eco-Linc (KEL) area using remote sensing technique and medium resolution dataset such as satellite landsat imageries. The use of satellite imagery in this study is precedence for establishing historical land cover data for the construction of deforestation trend. This is toward establishing a baseline scenario, which is critical for REDD+ implementation [3]. Past studies have conducted a deforestation and land cover change in protected areas using Landsat satellite imagery [3][6][7]. Concurrently, the output of this study is to provide critical information and knowledge of key areas such as the undisturbed natural environment that vulnerable to threat. Eventually utilized it in a sustainable way for effective conservation effort and continues supply of natural forest for local well-being.

2. Methodology

2.1 *Study site*

The study site was conducted in two of Sabah's state larges terrestrial parks; the Kinabalu Park located at the north-eastern part of Kota Kinabalu, and Crocker Range Park where the range lies between Sabah's interior and west coast division, as well as KEL area that located in between both of the state Park that physically separated by approximately 10 km (Figure 1). The total size of study area is approximately 238274.83 ha for Kinabalu Park (76487.71 ha), Crocker Range Park (140529.05 ha), and KEL (21258.05 ha). Despite both Kinabalu Park and Crocker Range Park gazetted as state's park, some of the land within and adjacent to the park area entitled and claim by the local community that have been practicing traditional shifting cultivation. Thus, continuous negotiation and measures have been undertaken by the Sabah Park Board of Trustee to conserve and sustainably protect the state's park. However, a study by [8] shows that the existing protected areas in Borneo have failed to protect the existing highly connected forest. Hence, KEL area has been recognized as important ecological linkages that will enhance the connectivity between both parks. This area has altitudinal area that range from 300 m to 1700 m [9]. On top of that, conservation and CUZ integration were more feasible and effective in this area since there is pristine forest reserve (Tenompok Forest Reserve) located in between the park.

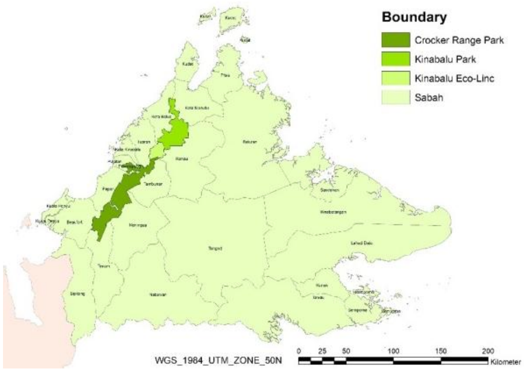


Figure 1 Location of Kinabalu Park, Crocker Range Parks and KEL area.

2.2 *Landsat data and pre-processing*

An overview of the methods used in this study is shown in Figure 2. Multi-temporal satellite data covering the study sites were acquired from the United States Geological Survey (USGS) EarthExplorer (see http://earthexplorer.usgs.gov/, Path/Row: 118/56). The landsat image obtained has 10 years' time interval frame and were obtained from the Landsat 5 Thematic Mapper (TM), Landsat 7 Enhance Thematic Mapper Plus (ETM+), and Landsat 8 OLI (operational Land imager) and TIRS (Thermal Infrared Sensor).

The satellite images from year 1991 was selected as a reference year of a base line as it has the most cloud free image and represents the early year of protected areas gazette in 1964 (Kinabalu Park) and 1984 (CRP). The image from year 2018 represents the latest observation of the study area.

Seven digital topographic map sheets covering the study site were obtained from the department of Survey and Mapping Malaysia (JUPEM). The map sheets at a scale of 1: 50,000 is updated information from 1978 to 1998. The purpose of this map is to analyses the training set during supervised classification for historical image processing [6]. High-resolution images that freely accessible also obtained from Google Earth. It is very convenient to support training area information during land cover classification process [6, 10]. Both topographic map and Google Earth engine was used for source of "ground-truthing" [3] and combine with the ground-truth field data.

To minimize the effect of geometric distortion, the dataset undergoes first stage of pre-process through radiometric correction. This correction involves conversion of image digital numbers to at-sensor radiance, conversion of image digital numbers to top-of-atmosphere reflectance with specified raster data type and scale, dark object subtraction and topographic correction [11]. Since the study sites located in tropical forest and high mountainous area, cloud covering on almost all the Landsat image is unavoidable. Hence, multiple landsat imageries were used to create a single cloud free image for each year. Cloud masking using Fmask algorithm to detect the cloud and cloud shadow and masked out of the images [12-15]. Histogram matching was conducted on all image of same scene to make the spatial display and pixel value between the images as close as possible [3, 7] before combining all the dataset using image mosaic processing.

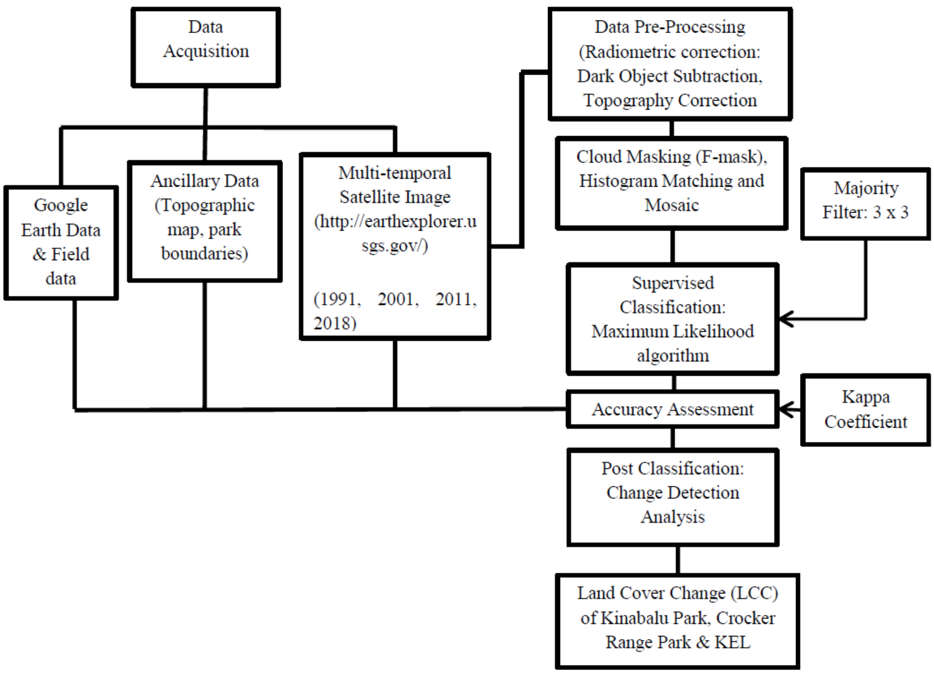


Figure 2. Flowchart of the land cover change map developed for the study.

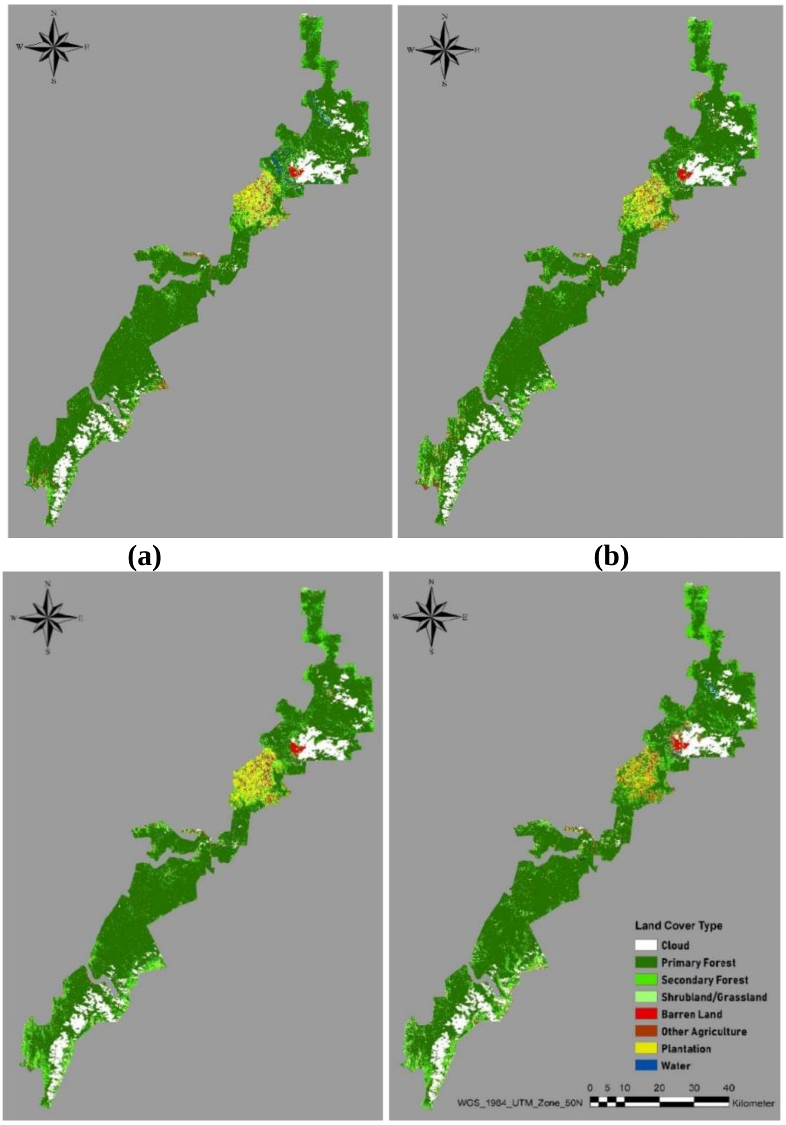
2.3 *Land cover classification and change detection*
Maximum likelihood classifier was used was used to create the land cover change map of both parks and KEL area. Via this method, pixel-based classification employed by digitizing a training area for each class detected. Using the training area sample, the computer system trained and recognizes the spectral signature of different types of land cover classes [6]. Seven classes of land cover classified were used and defined as: (1) primary forest, (2) secondary forest, (3) shrubland/grassland, (4) barren land, (5) other agriculture, (6) plantation, and (7) water. The description of the land cover classification is given in Table 1. Majority statistical filtering using 3 x 3 filtering was then applied to reduce the salt and pepper effect on the classified image (Kamlun *et al.* 2016). Accuracy assessment was then conducted on the entire classified image to accurately verify the degree of the accuracy for the classified image. This assessment used reliable reference point obtains from field work groundtruth point, digital topographic map and high-resolution Google earth image. Kappa accuracy assessment was employed since it is common and widely used for remote sensing field of study [7].

Post classification change detection was used to detect land cover change in the study site. Using this means of change detection, the total cloud cover of image for corresponding years was combined and mask out of every image classified. This to give equals cloud cover of land cover area for accurate land cover change detection. The changes of area in three different timeframes (1991-2001, 2001-2011, and 2011-2018) have been calculated.

Table 1. Classification scheme used to identify vegetation changes in the study area.

Class name	Description
Primary forest	Pristine forest; lowest altitude (700 m) Dipterocarpaceae (mostly Shorea spp.); middle altitudes (1700–2700 m on non-ultrabasic substrate and 1700 m on ultrabasic substrate), myrtaceous genera (Syzygium and Tristaniopsis dominant sp.), and *Dacrycarpus imbricatus* and *Dacrydium pectinatum*(Co-dominant); and highest altitudes (3100m/>3100m) *Dacrycarpus kinabaluensis* and *Dacrydium gibbsiae* dominant sp. [16][17]
Secondary forest	Disturbed pristine forest; secondary growth of young trees.
Shrubland/grassland	Herbaceous regrowth; Grassy vegetation includes tall forbs, mosses and lichens.
Other agriculture	Shifting cultivation; paddy hill, pineaple [16][17]
Plantation	Rubber plantation (Hevea brasiliensis); Oil palm plantation (Elaeis guineensis)
Barren Land (Bare land/road/settlement/ mountain top rock)	Areas of very sparse or no vegetation, characterized by outcropping rocks: built-up areas or “grey infrastructure’ (i.e., roads, settlements, and urbanization); transitional areas [6][18]
Water	River, stream and water catchment.

3. Result
3.1 *Land cover classification and accuracy assessment*
The preliminary result of land cover classification for year 1991, 2001, 2011, and 2018 are shown in Figure 3. The land cover map shows seven spatial information of land cover consisting primary forest, secondary forest, shrubland/grassland, barren land, other agriculture, plantation, and water. Based on the map, primary forest is characterised as the predominant land cover type while secondary forest, shrubland/grassland, barren land and water are commonly found in the entire site. Since the study sites are known to have historical shifting cultivation activities, other agriculture class also present in all site from year 1991 to 2018. It is also found that the plantation class are only present in KEL area from 1991 until year 2018. However, in year 2011 until 2018, plantation is detected and present in both protected state park.



(a) **(b)**

(c) (d)

Figure 3. Seven class of land cover classification for Kinabalu Park, Crocker Range Park, and KEL (a= year 1991, b=year 2001, c= year 2011, and d= year 2018) with minimum cloud cover (10%).

Validation on generated map is conducted using Cohen's Kappa accuracy assessment. By using the Google Earth Engine as well as the conducted field ground truth, a minimum of 50 point has been randomly generated for each respected year (Table 2(a), Table 2(b), Table 2(c), and Table 2(d)). The Cohen's kappa accuracy assessment shows high to moderate degree of accuracy value for year 1991, 2001, 2011, and 2018 (Table 3). The overall accuracy of land cover classification for year 1991 was 82.29 % with kappa coefficient of 0.79. Year 2001 shows the overall accuracy with 77.71 % and 0.74 kappa coefficient. Meanwhile, year 2011 has the lowest overall accuracy of 65.43 % and kappa coefficient of 0.60. Lastly, year 2018 shows the overall accuracy of 76.00 % with kappa coefficient of 0.72.

Table 2. Accuracy assessment for each respective year; (a) 1991, (b) 2001, (c) 2011, and (d) 2018.

Land Cover Class		Reference Point							*Total*	*User Accuracy (%)*
		PF	*SF*	*SF/GL*	*BL*	*OA*	*P*	*W*		
Classified point	*PF*	44	3	1			1	5	*54*	*81.48*
	SF	4	47	3			6		*60*	*78.33*
	SL/GL	2		44	3	7	5	2	*63*	*69.84*
	BL				45	11		3	*59*	*76.27*
	OA			2	2	31	1		*36*	*86.11*
	P					1	37		*38*	*97.36*
	W							40	*40*	*100.00*
Total		***50***	***50***	***50***	***50***	***50***	***50***	***50***	***350***	
Producer Accuracy (%)		*88*	*94*	*88*	*90*	*62*	*74*	*80*		

(a)

Land Cover Class		Reference Point							*Total*	*User Accuracy (%)*
		PF	*SF*	*SF/GL*	*BL*	*OA*	*P*	*W*		
Classified point	*PF*	47	8	2	2		1	5	*65*	*72.30*
	SF	2	34	5	1	1	1		*44*	*77.27*
	SL/GL		1	34	5	4	6		*50*	*68.00*
	BL	1			39	8	1	3	*52*	*75.00*
	OA		2	9		35			*46*	*76.08*
	P		5		3	2	41		*51*	*80.39*
	W							42	*42*	*100*
Total		***50***	***50***	***50***	***50***	***50***	***50***	***50***	***50***	
Producer Accuracy (%)		*94*	*68*	*68*	*78*	*70*	*82*	*84*		

(b)

Land Cover Class		Reference Point							*Total*	*User Accuracy (%)*
		PF	*SF*	*SF/GL*	*BL*	*OA*	*P*	*W*		
Classified point	*PF*	47	9				1	7	*64*	*73.43*
	SF		23		4	1			*28*	*82.14*
	SL/GL		10	32	2	1	8	3	*56*	*57.14*
	BL			8	31	9	2		*50*	*62.00*
	OA	1		5	6	27	8	1	*48*	*56.25*
	P	2	8	5	7		30		*52*	*57.69*
	W					12	1	39	*52*	*75.00*
Total		***50***	***50***	***50***	***50***	***50***	***50***	***50***	***350***	
Producer Accuracy (%)		*94*	*46*	*64*	*62*	*54*	*60*	*78*		

(c)

Land Cover Class		Reference Point							*Total*	*User Accuracy (%)*
		PF	*SF*	*SF/GL*	*BL*	*OA*	*P*	*W*		
Classified point	*PF*	45			1		7	5	*58*	*77.58*
	SF	2	45	8	5		4		*64*	*70.31*
	SL/GL	3	1	26	3	2	5	4	*44*	*59.09*
	BL			5	34	35		1	*45*	*75.55*
	OA			7	5	43			*57*	*75.43*
	P			3	1		34	1	*41*	*82.92*
	W			1	1			39	*41*	*95.12*
Total		***50***	***50***	***50***	***50***	***50***	***50***	***50***	***350***	
Producer Accuracy (%)		*90*	*90*	*52*	*68*	*86*	*68*	*78*		

(d)

[*]Note: PF – Primary Forest, SF – Secondary Forest, SL/GL – Shrubland/Grassland, BL – Barren Land, OA - Other Agriculture, P - Plantation, W - Water

Table 3. Cohen's Kappa accuracy assessment for each respective year (1991, 2001, 2011, 2018)

Accuracy measure	Year 1991	Year 2001	Year 2011	Year 2018
Overall accuracy, %	82.29	77.71	65.43	76.00
Kappa coefficient, κ	0.79	0.74	0.60	0.72

3.2 *Land cover changes*

From overall total land cover area (238,274.81 ha) in the study site only 237944.16 ha free from cloud covering. The entire generated LCC map is masked out with the same total area of cloud cover. Hence, the total cloud area combines for all the years from 1991 to 2018 approximately about 10 %.

Table 4. Land cover area in hectare (ha) for each corresponding year (1991, 2001, 2011, 2018)

Land cover type	1991	2001	2011	2018
	Area, Ha	Area, Ha	Area, Ha	Area, Ha
PF	170633.25	169211.88	168480.81	159863.58
SF	15090.3	17817.03	19834.84	24853.68
SL/GL	12392.37	11298.87	10117.08	12715.38
BL	3670.65	4507.56	2933.82	3850.74
OA	2320.2	2490.48	3136.32	3502.89
P	5313.87	5579.28	7188.48	5514.66
W	3038.22	1553.76	777.51	2157.93
TOTAL	237944.16	237944.16	237844.16	237944.16

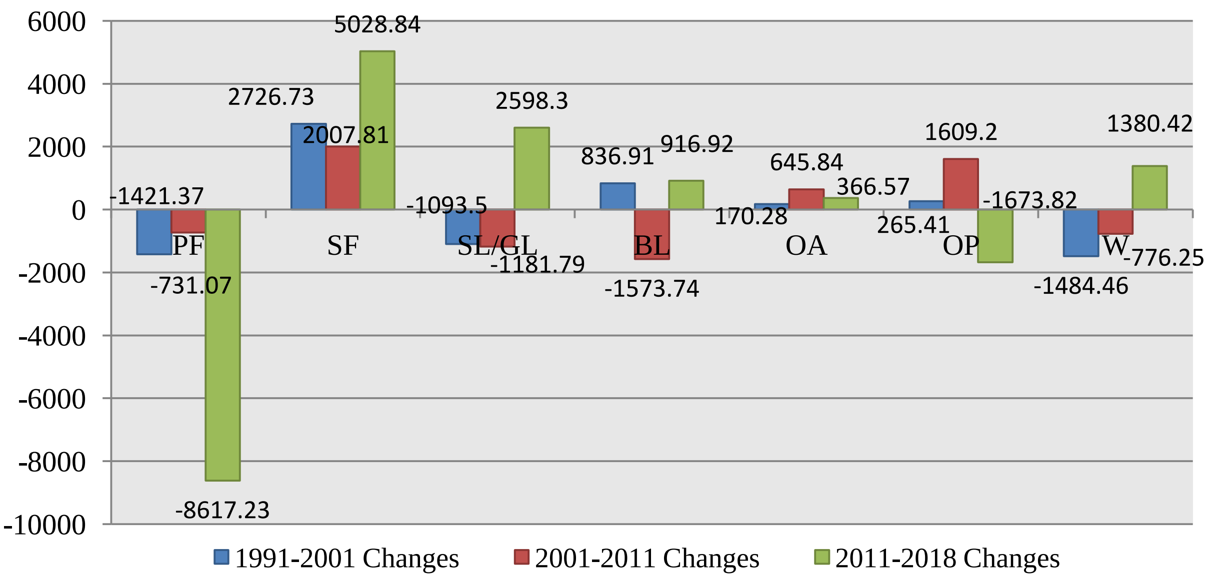


Figure 4. Land covers change area in hectare (ha) within three time frame (1991 – 2001, 2001-2011, 2011- 2018)

Based on Figure 4, a graph of changes on land cover area (ha) for year 1991 – 2001, 2001 – 2011 and 2011 – 2018 has been illustrated. In the past 28 years period, the predominant land cover class has shown drastic decline in primary forest. Between the years 1991 – 2001, primary forest class has shown moderate loss between years 1991-2001 and 2001-2011 by losing 1427.37 ha and 731.07 ha.

This change has continuously occurred in year 2011-2018 by drastic decline in forest area losing 8617.30 ha. The secondary forest shows a moderate increase in forest area between 1991 – 2001 and 2001 – 2011. This continuously increases double in years 2011-2018 with an area 5028.84 ha. Meanwhile, shrubland/grassland class both has decrease in area for years 1991-2001 and 2001-2011 by losing 1093.50 ha and 1181.76 ha. However, between years 2011-2018, the class area has increase by 2598.30 ha. Between the years 1991 to 2001, barren land has increased by 836.91 ha which later decrease in years 2001- 2011 by losing 1573.40 ha. In years 2011-2018 the area shows slight increase with 916.92 ha compared to year 1991-2001.

Since shifting cultivation has been traditionally practice in this area, the land cover class for OA shows moderate increase in area for year 1991-2001 (170.28 ha), 2001-2011 (645.84 ha), and 2011-2018 (366.57 ha). Based on conducted field ground truth, plantation area specifically in KEL area is characterised by rubber plantation. This land cover type has shown a slight increase between years 1991-2001 (265.41 ha) and drastically increase by 1609.20 ha in years 2001-2011. Despite that, almost same amount of plantation area has lost in the years 2011-2018 timeframe. Meanwhile, the changes in land cover area of water illustrate moderate decline both in years 1991-2001 and 2001-2011 by losing 1484.46 ha and 776.25 ha. Lastly, in year 2011-2018, the water class has increase by 1380.42 ha.

4. Discussion

4.1 *Accuracy assessment*

The accuracy assessment exhibited that the kappa coefficient value of land cover classification map for each respective year has high to moderate value of accuracy. Year 1991 has the clearest and cloud free satellite imagery compare to the other images of respective years. Hence, based on the accuracy table, land cover classification in year 1991 has highest overall accuracy and kappa coefficient. Low accuracy value on generated map usually associated with misclassification. Logically, misclassifications of land covers are often due to confusion on the spectral signature of land cover class. The utmost contribution of this problem is from haze which can alter the spectral signature of landsat image [19]. For example, confusion between primary forest and secondary forest, shrubland/grassland as well as barren land and water. Past study on land cover classification using landsat imagery also experience similar problem [3]. In addition to that, the confusion of primary forest and secondary forest especially in high topography area is suspected to be due illumination condition that influences the quality of corrected image. This is due to different illumination condition could cause different topographic correction for each landsat image [20]. Hence, contributed to more misclassification on landsat images. It is hard to produce high kappa coefficient accuracy using medium resolution satellite imagery especially for highland and mountainous area due to these factors. Hence, this limitation could be improved by using more high-resolution image that are cloud free and suitable topographic correction.

4.2 *Land cover change*

The spatial changes that occur in Kinabalu Park, Crocker Range Park and KEL area are potentially driven by both natural and anthropogenic factors. This preliminary study has found that the primary forest located within a protected state's park and the area connecting both this park has drastically decline throughout the 28 years period. In years 1991-2001 timeframe, primary forest has been loss due to the forest fire that occurs within the parks boundary that happen during El Nino in year 1998 [21]. Hence, contributes to the loss of 1421.37 ha of primary forest. The continuous decline in primary forest also associated with conversion of agricultural and plantation area. Evident shifting cultivation activities near and within the park boundary specifically in Kinabalu Park also occur as it has been confirmed through field ground truth data. In the year 2011-2018, the drastic loss of primary forest might be associated with the earthquake that takes places in the year 2015. This also explain the increase of barren land area between year 2011 to 2018. However, it is not been confirmed that the event contribute majorly on the loss of primary forest as misclassification primary forest and secondary forest class might occurred. The increase secondary forest area is also might be associated with the conversion from shrubland and barren land.

Moderate increase in other agriculture class indicate that local people still relying and practice the traditional shifting cultivation as their living resources. Paddy hill is found to be a major shifting cultivation followed by pineapple field in KEL area [9]. Even though, agricultural activities are strictly prohibited within the state's Park, multi-temporal high-resolution image from Google Earth Engine has raise suspicious evident that the park might exhibit plantation class. Field ground truth data on these locations were unable to be obtain due to difficulties to access the area within the park. However, the utilization of remote sensing image and technique has provided a significant information on the spatial changes that occurred in the state's park and KEL area. The spatial information obtain is alarming especially with the continuous decline of primary forest that associated with land conversion. Hence, the generated information could provide significant spatial information for land use planning as well as tools for effective conservation effort in both state's park and KEL area.

5. Conclusion

The spatial changes that occur throughout the 28 years period within state park and KEL area are not solely drive by anthropogenic activities. However, continuous land conversion without proper planning and supervision by the related organization could seriously lead to deforestation within and surrounding the protected park. To support the increase in local population and their demand, the natural environment underwent changes for their welfare improvement. Hence, provide a potential threat on the natural environment and hindered the effectiveness of conservation plan. The preliminary indicates the reliability of the map to provide useful spatio-temporal data to locate key areas that important for sustainable natural resources and for effective conservation effort such as the undisturbed primary forest. However, due to limitation of using medium resolution landsat imageries, some of the land cover within the study site was not accurately classified. This is due to haze and topographic influence as well as the availability of cloud free image. The area covered by cloud resulted substantial land cover change left unknown. Hence, the use of more high resolution and cloud free image dataset is recommended for more accurate classification and land cover change detection. Lastly, continuous monitoring across the KEL site is important to better understand the trends in land use impacts as well as essential tools for effective implementation of REDD+ in the protected areas.

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