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MULTITEMPORAL HISTOGRAM MATCHING – A NEW APPROACH OF MOSS AND LICHEN CHANGE DETECTION FROM LANDSAT IN DATA-POOR ANTARCTICA ENVIRONMENTS

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Graphical abstract



Abstract

Mosses and lichens are important components of Antarctic ecosystems. Maps of these vegetation are needed to improve our understanding of ecosystem dynamics. This requires species distribution to be mapped repeatedly over time, a critical task that becomes extremely challenging in data-poor Antarctic regions, where the lack of field data, logistics, coupled with scarcity of cloud free, quality multitemporal Landsat imagery are major intrinsic constraints to time-series analysis for change detection. This study firstly analyzes the spectral curves of moss and lichen generated by field-based spectroradiometer and then proposes an innovative histogram matching technique where historical Landsat data is modified such that its histogram matches that of present (reference) dataset. This has made it possible to mapping multitemporal Landsat data in the Antarctic Peninsula. The results demonstrate an overall accuracy of 90.5%. Mapping of Arctic vegetation facilitated by histogram matching of Landsat image, according to the results, seems to be an advisable image processing technique for application in a datapoor context.

Keywords: Snow vegetation, multi-temporal, multispectral, Antarctica Peninsula, satellite, climate change

Abstrak

Lumut dan lichen adalah komponen penting dalam ekosistem Antartika. Peta tumbuhtumbuhan ini diperlukan untuk meningkatkan pemahaman kita tentang dinamik ekosistem. Ini memerlukan pada pemetaan taburan spesies dari masa ke masa, tugas kritikal yang dan sangat mencabar di Antartika yang miskin-data, dimana data lapangan sangat terbatas, logistik yang sukar, disamping kekurangan imej multitemporal Landsat yang berkualiti tinggi adalah kekangan utama untuk analisis siri masa untuk pengesanan perubahan. Kajian ini menganalisis lengkung spektrum lumut dan lichen yang diperolehi dari cerapan spektroradiometer di lapangan bagi teknik pemadanan histogram yang inovatif bagi data satelit sepadanan. Ini membolehkan untuk memetakan lumut dan lichen dari data Landsat multitemporal di Semenanjung Antartika. Hasilnya menunjukkan ketepatan keseluruhan 90.5%. Pemetaan tumbuh-tumbuhan Artik kaedah pemadanan histogram imej Landsat, disaran sebagai teknik pemprosesan imej bagi aplikasi dalam konteks keterbatasan data.

Kata kunci: Tumbuhan salji, multi-temporal, multi-spektral, Semenanjung Antartika, satelit, perubahan iklim

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1.0 INTRODUCTION

The Antarctic Continent and Peninsula hosts a significant number of microflora such as fungi and algae, and primary producers predominantly cryptograms such as mosses and lichens [1]. Life on the Antarctica's cold environment is considered highly sensitive to climate change [2], and therefore species distribution and changes of their abundance are considered as global climate change indicator [3], [4]. The spatial distribution, extent and spatiotemporal changes of these vegetation in the Antarctic have received considerable attention in recent years [5]-[7]. Knowledge about distribution and cover changes over the years of moss, algae and lichen on Argentine Islands is very scarce [5], [8], while this information particularly with regard to climate changes is essential for conservation of Antarctic's floral communities [9]. Maps of vegetation characteristics are needed to improve our understanding of species dynamics and Arctic ecosystems.

The Argentine Islands include isolated land masses with group of true islands or fragments of ice-free ground separated by ice. Satellite remotely sensed data with its synoptic viewing and repeatability of data acquisition over the specific target-of- interest offers best source of data for assessing spatiotemporal changes of vegetation for the remote and isolated areas such as in Antarctic Peninsula (AP). Recent development in remote sensing techniques has allowed producing large-scale topographic mapping series by the British Antarctic Survey (BAS) and the United States Polar Studies. In addition, spectral transformations of remote sensing data, particularly the red and infrared bands with selected vegetation index (VI) are used for extracting and mapping vegetation-related information in the Antarctica region [10]. From the previous studies, even though the ability of Landsat imagery for spatiotemporal change detection is well demonstrated [11]-[14], scarcity of cloud-free images [15], lack of field data, and logistics, are major intrinsic constraints to time-series analysis for change detection.

In this paper, we report the change detection mapping of moss and lichen-dominated vegetation over AP. The window for sun-synchronous orbiting satellite for the Arctic regions is quite limited, and possibility of having cloud-free image is scarce, especially over the AP. Moreover, field visits to these remote areas are very costly and, therefore, direct measurements of target vegetation occurrence data are available for few sites only. While multitemporal image analysis is based on collecting field data corresponding to the image acquisition days, and remote sensing specialists tend to collect data during satellite overpass times to calibrate sensor data and to test accuracy of the methods. Consequently, optimizing archived multi-temporal Landsat data with field observations is the only best approach for mapping change detection. We highlighted an approach of histogram matching of archived multitemporal to the latest corresponding image acquired during the field observations. Based on histogram matching of recent Landsat data, it can be assumed that historical imagery could be used for matching histogram to the recent image and assist detection of target vegetation both from recent and historical images from the Normalized Difference Vegetation Index (NDVI) [16].

NDVI is the simple indicator of vegetation parameters such as percent cover, leaf area index and biomass. Realizing the usefulness of NDVI to assess vegetation changes, previous studies used NDVI derived from both field and satellite observations (MODIS) [17]–[19] for vegetation productivity analysis of Arctic Alaska and northern hemisphere or used LIDAR-derived shrub canopy metrics and imagery spectral metrics for studying shrub biomass of Arctic tundra [20]. Hence, this study also used NDVI as a useful proxy of moss and lichen for this Antarctic ecosystem.

This study is a part of extensive expedition over Antarctic conducted by a team of researchers of Universiti Teknologi Malaysia (UTM) in the late summer, February to March 2015 [21]. With multi-disciplinary UTM-Antarctic mission team, this study aimed at investigating potential image processing technique applied to multitemporal images to make them useable and to make mapping moss and lichen changes possible in the data-poor areas of AP.

2.0 METHODOLOGY

The study was conducted in Argentine Islands covering 51.91 km², located in the western part of the AP (Figure 1). The land is under an ice sheet [22]. The climate of the region ranges from a subpolar climate in the north to a polar climate in the south. The region has an extremely cold climate with mean temperatures below 0°C (32°F) with frost and snowfall occurring throughout the year. Temperatures are always low in the region; during the polar night in winter, temperatures drop down to -42°C (-44°F). In the warmest month, mean temperatures are usually below 0 °C (32 °F). Precipitation mainly falls as snow. Due to the ice sheets and alaciers covering most of the region and the severity of the climate, the flora is sparse and limited only to coastal areas [23], [24].

After an exhaustive search of Landsat archive, two Landsat 7 Enhanced Thematic Mapper (ETM+) and one Landsat 8 Operational Land Imager (OLI) acquired on September 2, 2009, March 12, 2011 and February 27, 2015 respectively were found useable, which were downloaded from the United States Geological Survey (USGS; http://earthexplorer.usgs. gov/). They had less than 10% cloud cover within areaof-interest, and no cloud cover over the targeted objects (moss and lichen cover).

Field data on spectral radiometry were collected for moss (n = 40) and lichen (n = 40) using portable ASD spectroradiometer, with 3 nm spectral resolution in the visible to very near infrared range (400 – 1000 nm). Snow-covered rock outcrops, coastal cliff and large floating icebergs are main habitats of moss and lichen. Locations of moss and lichen were recorded using handheld GPS.



Figure 1 Study site and locations of in-situ data collection ampling points. *Source* [21]

Five commonly used image pre-processing activities were performed in this study: 1) creation of image subset and geometric correction, 2) conversion of raw digital numbers (DN) to top-of-atmosphere (TOA), 3) histogram matching, 4) extraction of NDVI and mapping, and 5) accuracy assessment and change detection. Radiometric correction was performed following Landsat ETM+ and OLI reference manual [25]. All the image sets were geo-referenced to corresponding map of the area to minimize geometric distortions inherent to the image. Recent British Antarctic Survey (BAS) map was used for this purpose. The image was geo-referenced to the UTM coordinate system, datum WGS-84 area 48N using a total of 35 ground control points (GCP) which are identifiable in the satellite image and the corresponding BAS map of the study area such as base camp, island's bay, isolated island and water. Coordinates of these GCPs were refined with GPS surveys while target on satellite and corresponding target on BAS map was matched using second-order degree polynomial function. Less RMSE (0.3628 m) indicates good geometric correction result is obtained where the error of geometrically corrected image is much smaller than 1/3 of Landsat's pixel size. The geometrically corrected images were resampled to 30 m Landsat pixel size using nearest neighbor approach to preserve the pixel intensity of correspond features on the Landsat image.

Next, recently acquired OLI (2015) was radiometrically calibrated using field spectroradiometer observations (Figure 2) where in-situ spectral observations; the respective bands were compared and adjusted by the gain and offset, derived from ground-to-air relations:

$$\Lambda_i = G_{S_i} + C_i \qquad (1)$$

where Λ_i is the calibrated reflectance band *i* (i= red and NIR bands), G is the gain coefficient for band *I*, S_i is the spectral reflectance of corresponding band i measured with spectroradiometer, and C_i is the offset coefficient for band *i*. Note that, since extracting NDVI requires red and near-infrared (NIR) bands, image histogram matching was applied these two bands and other bands were not used for this study.

Histogram matching was applied to two historical images acquired 2009 and 2011, where several homogeneous substrates where NIR completely absorbed and tends to become 'zero' such as deep ocean locations were used for histogram matching purpose. objects such as the calibrated image acquired in 2015 was used as reference image to match the rest ETM+ 2009 and 2011 because these historical images were acquired close to the field data collection dates and the radiometric quality was superior (minimal value is 0, showing less affected by cloud and haze impurities). The histogram matching technique was applied on the all bands of interest of each 2009 and 2011 scene. Let b_j^t , j = 1, ..., m as jth band while superscript t denoted the band from targeted scene whose atmospheric impact is in control and feature objects were identified locally. b_{ii} , i = 1, ..., n; j = 1, ..., m is assumed as the *i*th scenes, from *ith* band.



Figure 2 a) Spectral signatures of b) moss and c) lichen, based on field spectroradiometer observations in Argentine Islands

The targeted scene was used as the reference for the histogram matching. Let the relationship between *j*th bands for a feature of targeted and *i*th scene be linear. m_{ij} and c_{ij} are the gradient and intercept respectively. Then,

$$b_{ij} = (b_j^t \times m_{ij}) + c_{ij} \tag{2}$$

Further, for histogram matching, the slope and intercept of b_{ij} , $i \ge 1$, $j \ge 1$ varies similarly as b_j^t , $j \ge 1$. Therefore, the new band, b_{ij}^{new} was retrieved as:

$$b_{ij}^{new} = (b_{ij} \times m_{ij}) + c_{ij} \qquad (3)$$

Prior to histogram matching, caution should be taken for the image data sets if those are of different quantized (bits). Since OLI possess 16 bits and ETM+ had 8 bits, those should be of same quantization. For this study, OLI data were downscaled to ETM+ (255 grey-scale) following linear quantization.

Post-histogram matching check was performed through regression analysis between red and NIR bands of 2015 image with 2009 and 2011 images, respectively (Figure 3). The histogram matching process completed with greater accuracy as indicate by R²>0.9.

After histogram matching of red and NIR bands of 2009 and 2011 data, extracted NDVI. The NDVI for ETM+ and OLI were calculated using following equations, respectively.

NDVIIM=(band4-band3)/(band4+band3)	(4)
NDVIoLI=(band5-band4)/(band5+band4)	(5)

The NDVI retrieved from OLI 2015 were then used for detecting vegetated and unvegetated classes. Field data point-location and corresponding image data were used as seed training points for image classification for the study area. This was performed using Region Growing Segmentation algorithm in the ENVI 5.0 digital image processing system. The thresholds of NDVI range for specific class were main input in region growing process, with strict tolerance of standard deviation of < \pm 0.0001 for each iteration, until full convergence. The segmentation process was then repeated for 2009 and 2011 normalized image data. Table 1 summarizes the ranges of NDVI used for thresholds in segmentation of recent and historical images.



Figure 3 Post-histogram matching check; correlations between reference image OLI 2015 and ETM+ 2009 (a and b) and ETM+ 2011 (c and d)

The segmentation accuracy was assessed using 80 independent field data. An overall (OA), producer (PA) and user accuracies, and kappa values were calculated.

3.0 RESULTS AND DISCUSSION

The correlation of calibrated Red and NIR versus corresponding field data was strong (R²>0.9) for targeted features. It implies that the normalized value of Landsat ETM+ is highly correlated with Landsat OLI $(\mathbb{R}^2 > 0.9, p \le 0.001)$ (Figure 3). Also, histogram matching process of pixel value of Landsat ETM+ (8 bits) is important and it should be close to Landsat OLI (16 bits) for more accurate histogram matching for all Landsat sensors. It has possibly led to variations in signal and less light absorption in NIR band, and consequently, tend to show similarity with corresponding DN in Landsat OLI 2015. To ensure the better performance of image histogram matching, the reflectance values between red and NIR (both bands are used in NDVI) on Landsat ETM+ should be close to reflectance values of Landsat OLI.

Moses are spectrally distinct from Lichen, particularly at NIR wavelengths (Figure 2). This NIR distinction was also present at Landsat's spectral resolution, while discrimination could not be made at the visible wavelengths.

Table 1 NDVI thresholds used in this study for implementation of region growing process; estimated moss and lichen cover and changes over times

	Moss			Lichen		
	2009	2011	2015	2009	2011	2015
NDVI range	0.083-0.131	0.083-0.131	0.188-0.348	0.077-0.085	0.076-0.085	0.040-0.085
NDVI mean	0.102	0.102	0.265	0.080	0.080	0.052
Area (ha)	17.1	20.61	27.72	6.12	8.28	15.39
Percentage of total study area	2.8	3.37	4.54	1.00	1.36	2.52
Percent cover change per year	-	10.26	8.62	-	17.65	21.47

This confirms the justification of red and NIR wavelengths used for transforming them into NDVI for mapping snow vegetation (SV) compared to subtidal vegetation with low NIR signal [26]. Most studies dealing with detecting vegetation in Antarctica, including mosses and lichens, are based on NDVI analysis. Similar to this study (Table 1), others used NDVI for vegetation mapping in AP [27]. While it has been reported that detecting lichens using NDVI failed even in the extensively lichen covered areas [28]. However, this study used an alternative technique for detecting moss and lichen from Landsat imagery is regional growing algorithm where NDVI values were used as seed pixels and provided classified images with acceptable accuracy.

Overall mapping accuracy and K values were 90.5% and 0.806, respectively (Table 2), indicating satisfactory vegetation classification approach adopted in this study. Seed pixel growing technique used also found effective for mapping seagrass meadows in Malaysia [11], [29].

Table 2Classification accuracy achieved using histogrammatching for change detection of moss and lichen inArgentine Islands

	Producer's accuracy (%)	User's accuracy (%)	Overall accuracy (%)	Kappa co- efficient
Moss	93.3	80.0	90.5	0.8062
Lichen	86.7	83.3		

Distribution of moss and lichen and changes over the study sites during 2009-2015 are illustrated in Figure 4. Changes have been expressed in a) increase, b) decrease and stable state of vegetation. Although there was no general pattern of yearly changes observed in AP, the most distinctive areas of increasing trend in moss occurrence were around south and south-eastern areas, while lichen occurrence were around north AP throughout the study periods. Most of the mosscovered areas were stable between 2011 and 2015. Increase in lichen vegetation were observed in scattered locations (Figure 4).

A quantitative analysis of vegetation coverage (ha), density expressed as percentage of total Argentine Island and cover change per year (%) is given in Table 2. In general, there was an increase in spatial cover of all vegetation types. Among vegetation-types, moss had the largest (about 84% per year) spatial cover change from 2009 to 2011.

Patterns of changes over time in mosses also demonstrate substantially different change states (increase, decrease and stable), with some locations showing an increase and little decrease and others indicating stable (Figure 4). This could be due to either multiple colonization events or antiquity of moss population [30].



Figure 4 Assessment of the spatial distribution of moss (top) and lichen (bottom) from 2009-2015 in Argentine Islands

Spectroscopic capability of optical remote sensing variant offers larger and continuous mapping of SV that provides better insight about the growth, environmental dependent, population and physical character at different spatial and temporal scales. Such information could be deduced by spectral imagery of the Landsat missions giving potential of VI to radiometrically distinguish the SV from snow reflectance regardless of comprehensive radiometric correction routine. Future study could deploy other type of band-ratio variant such as normalized difference snow index (NDSI) to completely minimize the spatial impairment of mixed snow-vegetation pixels particularly in medium spatial resolution of Landsat mission [31]. Special attention should be considered to surrogate spectral discrepancy on Landsat band by using spectral correlation analysis. addition, application of higher resolution In microwave sensor may complement in numerically inferring the physical attribute of SV feature and thus, synoptic map of moss and lichen in AP at finest pixel resolution can be offered.

4.0 CONCLUSION

Owing to relatively poor sampling across the moss and lichen occurring areas of AP it is not possible to apply traditional image classification approach and consequently, impossible to discern whether any systematic changes characterize the variation in change states. Therefore, histogram matching technique proposed in this study could be a useful tool to make satellite imagery analyzable, especially for vegetation change detection in the data-poor areas. The field spectral radiometry adopted in this study has led to air-to-ground correlation of the corresponding satellite data and allowed multitemporal change analysis. The histogram matching process adopted for multi-temporal Landsat data sets can be used for other satellite images having similar spatial and radiometric attributes and foresee the future changes in data-poor areas. This will contribute to effective use of big data in improving our knowledge in ecology and environment of Antarctic. Satellite data sets can then be used to derive SV occurrences over exposed rock, cliff and on 'static-large ice-bergs. This technique can be used for monitoring SV cover changes and enhance our understandings on climate change impacts on SV and associated communities.

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