REMOTE SENSING DATA RESTORATION TO COMPENSATE FOR HAZE EFFECT

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ABSTRACT

Remote sensing data recorded from passive satellite system tend to be degraded by attenuation of solar radiation due to haze. Haze is capable of modifying the spectral and statistical properties of remote sensing data and consequently causes problem in data analysis and interpretation. Haze needs to be removed or reduced in order to restore the quality of the data. This study aims to restore the hazy data using proposed haze removal technique and evaluate its performance by means of spectral and statistical methods. In this study, initially, haze radiances due to radiation attenuation are removed by making use of pseudo invariant features (PIFs) selected among reflective objects within the study area. Spatial filters are subsequently used to remove the remaining noise causes by haze variability. The performance of hazy data restoration was evaluated using Support Vector Machine (SVM) classification. It is revealed that the technique is able to improve the classification accuracy to the acceptable levels for data with moderate visibilities and restored the spectral and statistical properties of the data and shows an increase in overall classification accuracy from 51.63% to 82.62%.

Keywords: *Haze Removal, Land cover Classification, Landsat 8, Support Vector Machine, Spectral, Statistical*

1. INTRODUCTION

Haze is a partially opaque condition of the atmosphere caused by tiny suspended solid or liquid particles in the atmosphere [1-3]. Malaysia experiences haze occurrences almost every year and are mainly caused by smoke originated from open fire in Indonesia due to plantation clean-up activities for the upcoming planting season [4]. Haze degrades the quality of data recorded from remote sensing satellite by modifying the spectral and statistical properties of the data [5-6]. This causes problems to remote sensing data users particularly in the case where continuous data is required for planning future actions such as in precision agriculture (PA). The impact is worse especially for short-term crops for instance paddy which has been the staple food for the population in many parts of the world. The study reported in this article attempts to address the following research questions, i.e. what are the parameters required to compensate haze effects, how this can be done and how to measure the accuracy of the haze removal? Basically, there are two main approaches of hazy data restoration methods commonly discussed in literature. The first method is an absolute correction method which is based on radiance transformation model. The second method is a relative method which is based on the properties of the hazy image itself or several images from different acquisition dates. Image based hazy data restoration method is an atmospheric correction method which is done by normalising an image to a reference image in order to remove atmospheric variation due to haze. The former method relies heavily on the availability on in-situ haze information which in certain is unavailable due to the location and lack of infrastructure. The second method on the other hand is depending too much on the properties of the remote sensing data that can lead to serious inaccuracy. Here propose a moderate approach which take into consideration of both methods. Before proceeding further, here we brief glance through several work carried out related to the issue of concern.

Liang et al. [7] introduced mean reflectance matching methods to remove haze. This is done by subtracting mean reflectance from the clear region of Landsat TM bands 1, 2 and 3 (visible bands). In performing this, they assumed that bands 4, 5 and 7 (infrared bands) are not affected by haze. The method seems most suitable for data with thin haze since under thick haze, infrared bands are also tend to be affected by haze. The study showed that the method is able to remove most haze but no in-depth evaluation was carried out pertaining to the statistical properties of the restored data.

Zhang and Guindon [8] developed haze optimized transform (HOT) to detect haze and further removed the haze layer by incorporating dark object subtraction method [9]. Moro and Halounova [10] further improved the method by adding HOT masking not only for dense vegetation but also for water and man-made features. The proposed method was applied on high resolution satellite data (IKONOS) and evaluated by means of vegetation index (VI) of both hazy and dehazed data. Hu et al. [11] developed haze detection, perfection and removal module coded in IDL language. Users can pick any method contained in each step or develop and use their own methods. Among the methods used for haze detection is HOT and dark object subtraction (DOS) for removal of haze. The methods were tested on a number of Landsat TM and QuickBird satellite data in which successfully reduced the effects of haze. Although the improve methods is autonomous and has taken into account of inhomogeneous haze, these methods still suffers from the disadvantage of dark object as there is a need to have dense vegetation within the scene.

Hu and Tang [12] carried out relative radiometric normalization (RRN) for atmospheric correction of remote sensing data. They normalised a hazy image based on a reference image that was free from haze. RRN used assumption that the relationship between the radiances recorded at two different times are homogenous and can be approximated by linear functions. For this purpose, pseudo invariance features (PIF) consisting of manmade objects, such as road lane, rooftop and parking lots, were determined from the scene within the data. The normalisation made use of a regression equation in which is developed by establishing relationship between the values of the PIF from both data. The relationship can be described as DN = a + b * DN. Where b is the multiplicative component which can correct for the difference in sun angle. The intercept a is an additive component which is able to correct the difference in atmospheric path radiance between the data sets. The important step in establishing the regression relationship is to obtain the a and b parameters. The method was able to remove most haze from the data, however robustness of the method when applied on different land covers is not tested. This is critical since the performance of removal method can be easily influenced by the underlying land covers. The subsequent subsections therefore attempt to identify the important parameters to remove haze, develop a suitable haze removal technique and evaluate the performance using suitable performance measures.

2. DATA INFORMATION

The study area is located at Bandar Puncak Alam in the district of Hulu Selangor, Selangor, approximately within longitude 101º 18’ 55.82” and 101º 29’ 29.56” East and latitude 3º 17’ 39.58” and 3º 7’20.13” North. Two Landsat images were obtained from USGS website (USGS, 2015), i.e. hazy and clear data dated from 19th Sept. 2015 and 30th May 2015 respectively. The data from both dates are type LIT (Level 1 Terrain Corrected). The L1T data possess systematic radiometric accuracy, geometric accuracy by incorporating ground control points, while also employing a Digital Elevation Model (DEM) for topographic accuracy [13,14]. The information of the data is shown in Table 1**.** The topography of the study area is mostly flat and mostly covered with oil palm.

The hilly area within the scene is predominantly covered with forest and oil palm. The urban area is occupied by mainly school, residential and industrial buildings. Hazy (top) and clear (bottom) data are shown in Figure 1. Visually, it can be seen that the hazy data dated from 19th September 2015 are highly affected by haze. This is evident from the whitish regions throughout the scene. The haze appearance is inhomogeneous with thicker haze located at the bottom and top left of the scene while thinner haze located at the top right of the scene. The haze was drifted from a large-scale forest burning in Sumatra and Kalimantan, Indonesia. It can be seen that the false colour image is not that affected by haze since two of the displayed bands (bands 5 and 6) are infrared bands while only one is visible band (band 4). Infrared bands are much less affected by haze compared to visible bands.

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Table 1. Information of The Hazy and Clear Data

	Hazy data	**Clear data (reference)**
Landat scene ID	LC81270582015262 LGN00	LC81270582015150 LGN00
Data type	L1T (Level 1 Terrain Corrected)	L1T (Level 1 Terrain Corrected)
Sensor ID	OLI_TIRS	OLI_TIRS
WRS path	127	127
WRS row	58	58
Acquisition date and time (UTC)	19th Sept. 2015 03:28:33	30th May 2015 03:27:40
Malaysia Standard Time	11:28:33	11:27:40

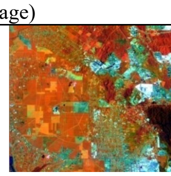
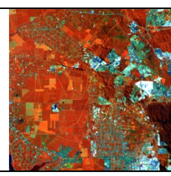
	Bands 2, 3 and 4 assigned to red, green and blue channel (true colour image)	Bands 5, 6 and 4 assigned to red, green and blue channel (false colour image)
(a)		
(b)		

Figure 1. Hazy Data (a) and Clear Data (b) with Bands 2,3 and 4 Assigned to Red, Green and Blue Channel (left) and Bands 5, 6 and 4 Assigned to Red, Green and Blue Channel (right)

The range of visibility was 6 to 8 km. This was consistent with the (Air Pollution Index) API value reported by Department of environment (DOE) at Klang station on 19th September 2015 at 11 am (Malaysian Standard Time) which was 92. This shows that the haze constituent is at moderate condition. This was also somewhat consistent with the visibility report provided by MetMalaysia at Subang station on 19th September 2015 at 11 am (Malaysian Standard Time) which was 4 km. This was likely due to the fact that Subang station is about 23 km from study area so the difference may be caused by meteorological factors such as wind speed and direction. Due to these factors, the visibility of the study area was taken as 6 to 8 km.

The data from 30th May 2015 were recorded during clear condition with API value reported by DOE at Klang station on 30th May 2015 at 11 am (Malaysian Standard Time) was 51 and haze visibility reported by MetMalaysia at Subang station on 30th May 2015 at 11 am (Malaysian Standard Time) was 14 km. Besides that, the data show no appearance of haze when displayed either in true or false colour images. Therefore, the data were regarded as clear data. The clear data were later to be used as the reference data in haze removal and accuracy assessment processes.

3. METHODOLOGY

The developed haze removal technique was applied on the hazy data. The flowchart for the haze removal is shown in Figure 2. Initially, the hazy data need to be pre-processed before carrying out haze removal. The datasets were L1T type and in 16 bit digital number [15]. The datasets were spatially subsetted to the area of interest. Spectral subset was done by selecting the bands of interest. Only bands 2 (blue), 3 (green), 4 (red), 5 (near infrared), 6 (shortwave infrared 1) and 7 (shortwave infrared 2) were selected for this study. Radiometric calibration was then carried out where pixels' digital number (unitless) is converted to radiance (W m^{-2} sr^{-1} μm^{-1}). This was done in ENVI software by making use the metadata that were provided together with the multispectral satellite data.

Haze removal and performance assessment processes were then carried out. In dealing with non-uniform haze, there are additional steps need to be taken into account in implementing haze removal process, i.e. we need first to identify the haze uniformity. If haze is uniform, we can proceed carrying out the normal haze removal technique. If haze is not uniform, segmentation of haze need to be done accordingly so that every segment has almost homogenous haze and eventually haze removal can be applied to the individual segments.

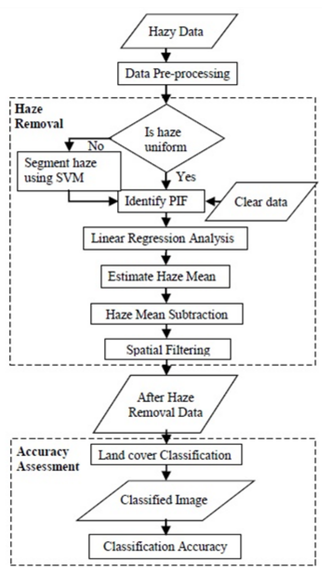


Figure 2. Flowchart for Haze Removal Technique

Liang et al. [16] used unsupervised classification to separate haze by clustering the pixels to an optimum number of clusters based on haze severity and produced segments that consist of different haze levels. Nonetheless, there are drawbacks in unsupervised classification, such as it tends to produce classification with low accuracy and may cause over-clustering where pixels are clustered into inappropriate number of haze segments. In order to overcome this problem, we implement a different method that makes use of visual inspection and supervised classification to produce classification with higher accuracy.

In carrying out this procedure, bands 4, 3 and 2 were first displayed in red, green and blue channel since the haze effects is more apparent in these visible bands. The bands were analysed visually to identify different haze severity regions. Training pixels were selected from the different haze severity regions. Classification was performed using support vector machine (SVM), a supervised method, to classify the hazy data into two haze severity classes viz. severe and less severe. Masks were produced from the classified image and subsequently applied to the hazy data to produce severe and less severe segments of haze. Figure 3 shows the hazy data together with the masks. Eventually, each segment contains uniform haze where haze mean is subsequently to be calculated and subtracted from each segment before performing spatial filtering. PIF was used in order to determine haze mean for each segment.

PIF were selected from both haze segments by selecting rooftops of residential and shop buildings. A linear regression relationship was then developed for the severe and less severe haze segments by making use of the PIFs from the hazy and clear data. The haze mean was subtracted from both haze segments for all bands. Subsequently, the severe and less severe haze from the hazy bands was combined where spatial filtering was next carried out. The hazy data dated from 19th September 2015 have moderate haze condition with 6 to 8km visibility. Higher classification accuracy was shown when implementing haze removal using spatial filter with kernel size 3x3 compared to 5x5. So, 3x3 kernel size was used for removing remaining noise due to haze variability. The accuracy differs mainly because the haze conditions in the simulated and real hazy data are different. In the simulated hazy data, the haze is homogenously distributed but in the real hazy data, the haze distribution is highly inhomogeneous. Figure 4 shows the true colour band combination of the clear and hazy data before and after haze removal side by side with the horizontal profile of the radiance value.

Visually, it can be seen that the data after haze removal shows less haze appearance compared to the data before haze removal. Besides that, the horizontal profile signifies that the radiance signatures for the data after haze removal were restored to almost similar to the radiance signatures of the clear data.

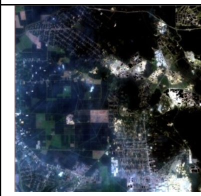
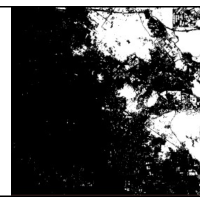
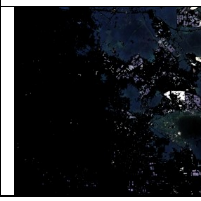
	Masking band	After mask data of bands 2, 3 and 4 assigned to red, green and blue channel
(a)		
(b)		

Figure 3: Masks (left) and The Corresponding Haze Segments (right) for (a) Severe Haze and (b) Less Severe Haze

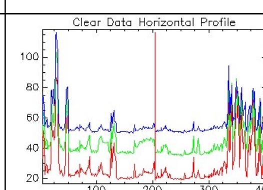
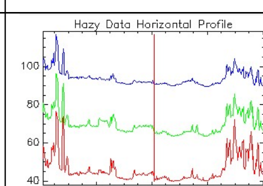
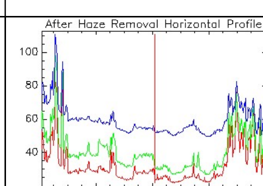
	Bands 2, 3 and 4 assigned to red, green and blue channel	Horizontal profile of the cross section.
(a)		
(b)		
(c)		

Figure 4: True Colour Band Combination of The Clear and Hazy Data Before and After Haze Removal. X and Y Axis Represent Sample and Radiance Respectively

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4. ACCURACY ASSESSMENT

Haze removal has been carried out to remove the effects of haze from remote sensing data and consequently to improve the quality of the data. In order to evaluate the performance of the haze removal, accuracy assessment of the haze removal need to be carried out using suitable performance measures; here we make use visual analysis and classification accuracy.

4.1 Accuracy Assessment of Clear Data

Initially, land cover classification on clear data was carried out. There are three types of land cover identified, with oil palm as the major land cover followed by urban and forest. The oil palm plantation is located at nearly flat and hilly areas on the left and upper right part of the clear data respectively. The forest on the upper right of the clear data seems highly encroached for replacement with oil palm plantation. This produces an appearance of oil palm plantation on hilly area with mix cultivation area between forest and oil palm regions. On the other hand the forest on the lower right part of the clear image seems not being encroached for any agricultural activities.

The urban area is mainly part of Bandar Puncak Alam area which consists of residential areas, shop lots, universities, factories and warehouses. Two different sets of ROI were selected for training and reference purposes. Training pixels were selected from three land covers with 179 pixels for forest (red ROIs), 122 pixels for oil palm (green ROIs) and 116 for urban (blue ROIs). A different set of ROIs was then selected to be the reference pixels for each land cover. SVM was used to classify the land covers within the scene by making use of the training pixels. The pixels selection was done based on our experiences, and with the help Google Map [17]. Besides that we are used to Klang area and the type of plantation in the study area. In implementing this, we make use of skills in image interpretation to identify various features like tone, textures. Pattern, shape, size and analyse association of each of the features [18]**.** The accuracy of the classification was assessed via confusion matrix, by comparing the classification with the reference pixels. Figure 5 shows (a) clear data with band 4,3 and 2 assigned to red, green and blue channel and (b) classified image using training pixels. Visually, it can be seen that SVM successfully classify the pixels into the right classes with oil palm (51.1%) as the largest land cover, followed by urban (28.6%) and forest (20.3%). As stated before, there are mixed cultivation areas on the right part of the classified image consisting of patches of forest and oil palm. Confusion matrices were used to assess the accuracy of the classification with respect to the reference pixels. It can be seen that almost all pixels were rightly classified into the respective classes with only one pixel from forest is misclassified as oil palm. The overall accuracy of SVM classification for the clear data is 99.76% with kappa coefficient of 0.9963 (Table 2).

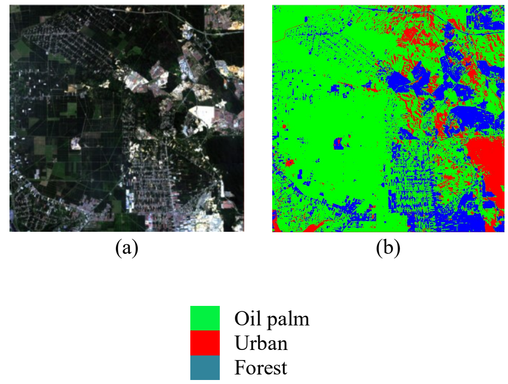

Figure 5: (a) Bands 4, 3 and 2 of The Clear Data Assigned to Red, Green and Blue Channel (b) The Classified Image of The Clear Data

Table 2. Confusion Matrix of The Clear Image in Terms of (a) Pixels, (b) Percent and (c) Producer Accuracy for Each Class in Terms of Pixels and Percentages

	Ground Truth (Pixels)			
Class	Forest	Oil Palm	Urban	Total
Forest	178	0	0	178
Oil Palm	1	122	0	123
Urban	0	0	116	116
Total	179	122	116	417

	Ground Truth (Percent)			
Class	Forest	Oil Palm	Urban	Total
Forest	99.44	0	0	42.69
Oil Palm	0.56	100	0	29.5
Urban	0	0	100	27.82
Total	100	100	100	100

Class	Producer Accuracy	
	(Pixel)	(Percent)
Forest	178/179	99.44
Oil Palm	122/122	100
Urban	116/116	100

Overall accuracy: 99.76% Kappa coefficient: 0.9963

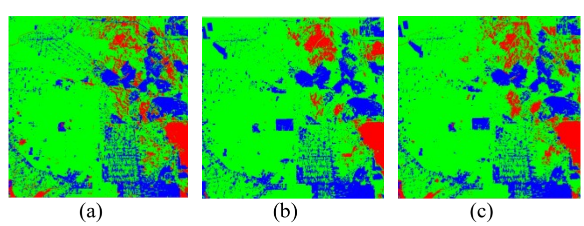

Figure 6: Classified Image of (a) Clear (b) Hazy Data (c) Hazy Data After Haze Removal

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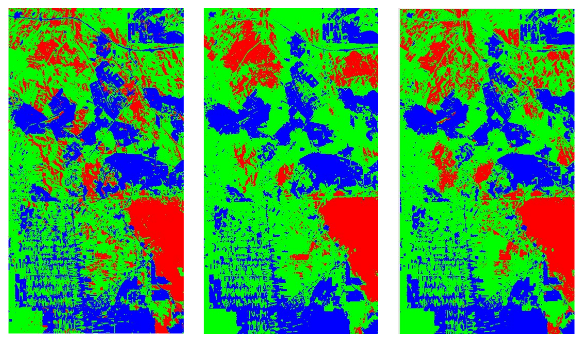
4.2 Accuracy Assessment of Hazy Data

The same set of training pixels were used for the hazy data in order to carry out SVM classification. For the purpose of visual analysis, the classified images for the hazy data before and after haze removal are shown together side by side with the clear data in Figure 6. Obviously, it can be seen that there occur some pixels misclassification between oil palm and forest within the hazy data before undergoing haze removal. Some urban pixels are also misclassified as oil palm. The misclassifications tend to occur because the appearance of haze causes modification of the pixel radiance value recorded by the satellite due to haze scattering and absorption. The data after haze removal show visual quality improvement and higher classification accuracy.

The misclassification between oil palm and forest seems have been reduced however not much improvement for the misclassification of urban area can be done by the haze removal. A clearer picture can be obtained by subsetting the classified image into a particular of interest in order to further analyse the hazy data after haze removal. The outcomes from subsetting the classified images to a smaller area of interest are shown in Figure 7. When making use the classification from the clear data as reference, the overall classification accuracy for the hazy data classification is 51.63% with kappa coefficient of 0.2 (Table 3). The producer accuracy for forest (30.17%), oil palm (66.19%), and urban (43.84%), is low, indicating that pixels misclassification is high for the hazy data. This is because haze layer has been affecting the radiance values (especially for bands 2, 3, and 4) and consequently causing a drop in the classification accuracy.

Table 4 displays the confusion matrix of the classified image for the data after haze removal. It shows that there is an increase of 31% in overall accuracy and an increase of 0.5 in Kappa coefficient. The overall accuracy and Kappa coefficient before - after haze removal are 51.63% - 82.62% and 0.2 - 0.7 respectively. This indicates that, the haze removal has successfully increased the classification accuracy of the hazy data. The producer accuracy for the classes is at acceptable and reliable level (i.e. 70% and above); for oil palm (87.18%) and urban (84.83%). Nonetheless, for forest (65.49%), the increase in producer accuracy is not up to the acceptable level since a large portion of the pixels were being misclassified as oil palm (33.56%) and urban (0.95%). In overall, the improvement of the classification is quite high and may be due to only three classes involved for this study area, resulting in a better restoration for the hazy data.

From the visual and classification accuracy analysis, the haze removal has successfully restored the spectral and statistical properties of the hazy data with respect to the clear data. Analysis on forest, oil palm and urban classes for clear, hazy and restored was done to examine the behaviour of their statistical and spectral properties. The statistical analysis covers the class mean, class standard deviation, class maximum and minimum value. All values are in radiance value (W m^{-2} sr^{-1} μm^{-1}) for each class and band. Figure 8 (a) shows mean radiance versus band for clear data, hazy data and hazy data after haze removal. By comparison there is a rise in class mean value for hazy data compared to class mean value for clear data. This is reasonable, because the effects of haze have modified the radiance values to new ones.



(a) (b) (c)

Figure 7: Subsetted Area of Classified Image of (a) Clear Data (b) Hazy Data (c)After Haze Removal Data

Table 3: Confusion Matrix of The Classified Image of Hazy Data with Respect to The Classified Image of The Clear Data In Terms of (a) Pixels, (b) Percent and (c) Producer Accuracy for Each Class

(a)	Ground Truth (Pixels)			
Class	Forest	Oil Palm	Urban	Total
Forest	13023	1328	2019	26370
Oil Palm	22648	63133	31254	117035
Urban	7499	20927	25977	54403
Total	43170	95388	59250	197808

(b)	Ground Truth (Percent)			
Class	Forest	Oil Palm	Urban	Total
Forest	30.17	11.88	3.41	13.33
Oil Palm	52.46	66.19	52.75	59.17
Urban	17.37	21.94	43.84	27.5
Total	100	100	100	100

(c)	Producer Accuracy	
Class	(Pixel)	(Percent)
Forest	13023/43170	30.17
Oil Palm	63133/95388	66.19
Urban	25977/59250	43.84

Overall accuracy: 51.63%, Kappa coefficient: 0.2

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Table 4: Confusion Matrix of The Classification After Haze Removal With Respect to The Classification of The Clear Data In Terms of (a) Pixels, (b) Percent and (c) Producer Accuracy.

(a)	Ground Truth (Pixel)			
Class	Forest	Oil Palm	Urban	Total
Forest	29089	10709	177	39975
Oil Palm	14905	95879	9293	120077
Urban	422	3388	52966	56776
Total	44416	109976	62436	216828

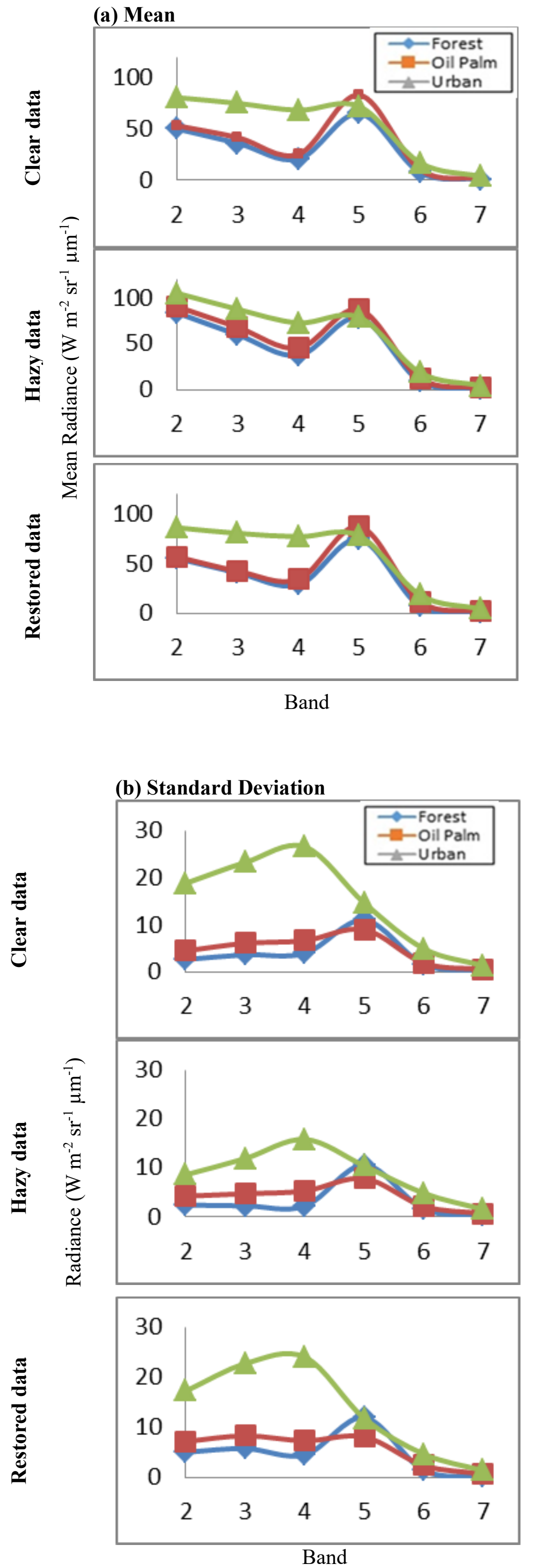
(b)	Ground Truth (Pixel)			
Class	Forest	Oil Palm	Urban	Total
Forest	65.49	9.74	0.28	18.44
Oil Palm	33.56	87.18	14.88	55.38
Urban	0.95	3.08	84.83	26.18
Total	100	100	100	100

(c)	Producer Accuracy	
Class	(Pixel)	(Percent)
Forest	29089/44416	65.49
Oil Palm	95879/109976	87.18
Urban	52966/62436	84.83

Overall accuracy: 82.62%, Kappa coefficient: 0.70

Other than that, it can be seen that visible bands (2, 3 and 4) are more likely affected by haze than infrared bands (5, 6 and 7). This is because the visible bands record reflectance in shorter wavelengths and more likely to be affected by the suspended matter in the sky during hazy condition rather than the infrared bands that can partially penetrate certain concentrations of haze. If haze is too severe the infrared bands can also be affected. This is also due to the fact that at 6 to 8 km visibility the data is moderately affected by haze. Mean radiance for oil palm and forest are close to each other but still slightly different. This is because oil palm and forest possess vegetation features of green colour but still can be separate to different classes by SVM classifier. Since the mean values for infrared bands was not that affected by haze, only the mean values for visible bands will be further discussed. It can be seen that overall mean radiances for all classes after haze removal have approached the mean value of the clear data. This shows that the haze removal technique has preserved the radiance signature of the classes during clear condition.

Standard deviation is a measurement of variability of data with respect to the mean [19]. As illustrated in Figure 8 (b), it can be seen that standard deviation for urban area is high for visible bands (2, 3 and 4). This is because urban classes consist of mixed pixels of residential area, plants around the residential area, roads, pavements, industrial area and landscaping plants. Pixels with high and low radiances were classified together as urban area resulting in higher standard deviation value.



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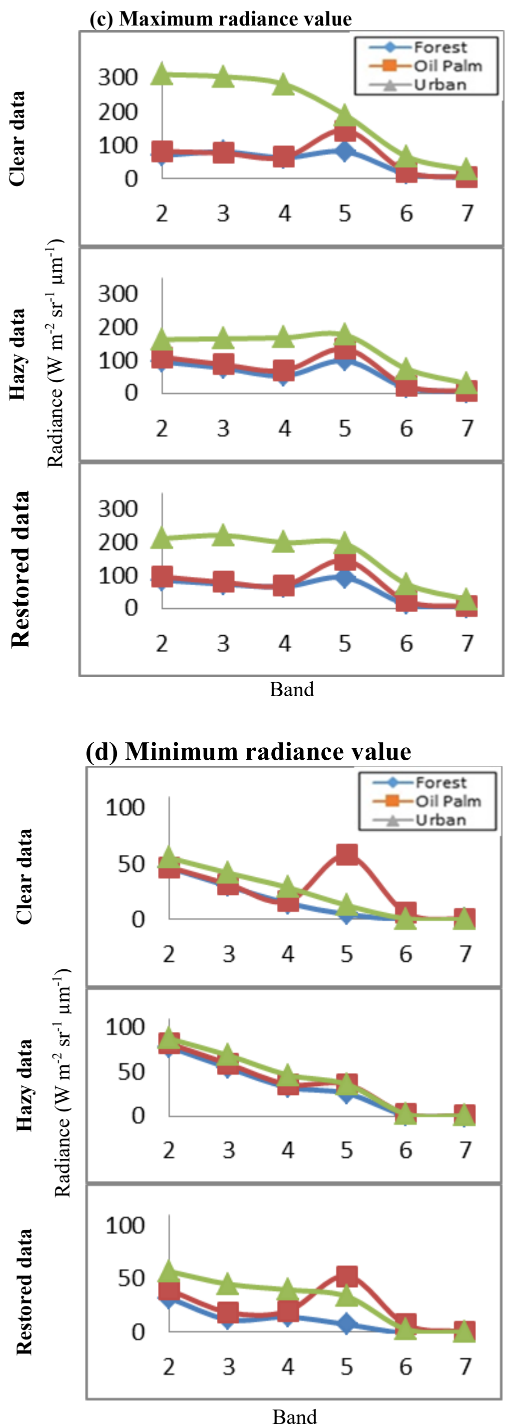

Figure 8: (a) Mean, (b) Standard Deviation, (c) Maximum and (d) Minimum Radiance Value of Landsat Bands 2, 3, 4, 5, 6 and 7 For Forest, Oil Palm and Urban From Clear, Hazy and Restored Data

On the other hand for oil palm and forest classes are mainly consist of pixels with low radiances that lead to lower standard deviation for almost all bands except for band near infrared (band 5) since infrared bands are the best at detecting green vegetation pixels. Overall, it can be seen that the standard deviation for infrared bands are not that affected by haze than the visible bands [20]. The standard deviation for urban in visible bands drop drastically for hazy data as compared to clear data and is restored after haze removal.

Comparison for maximum and minimum value between clear, hazy and restored data is also important to monitor if there is overcorrection [21]. The plots for maximum and minimum value are shown in Figure 8 (c) and (d) respectively. Overall it can be seen that the maximum and minimum values also have the same behaviour as the mean and standard deviation since the data after haze removal have the properties close to the clear data.

4.3 Improvement of the haze removal compared to previous works

The haze removal proposed in this study made use the combination of absolute correction and image-based approach. Haze removal task can be carried out efficiently by making use minimum knowledge on haze condition. The accuracy of the developed haze removal has been tested via SVM classification accuracy.

5. CONCLUSION

We successfully a novel developed haze removal technique and applied it to real hazy data with inhomogeneous haze, located in Selangor, Malaysia. The performance evaluation shows that the technique is able to remove most haze within the scene although there is still observable haze appearance after the haze removal process. The reliability of the haze removal technique is supported by the spectral and statistical analyses carried out on the restored data.

Based on the findings from this study, the following recommendations can be considered in future work; 1) The homogeneity of haze within remote sensing data is mainly due to topography and wind factors that need to be taken into account in developing a haze removal technique. 2) Haze segmentation need to be further studied so that is can be carried out autonomously in order to efficiently segment homogenous haze before haze removal can take place. 3) PIF selection need to be done autonomously where only minimal user interventions are required to avoid human error. 4) Haze removal technique need to be applied and evaluated in a more diverse land cover types to further evaluate the performance of the technique. 5) A suitable system need to be developed in order to embed the haze removal technique so that it is more practical to a wider range of users.

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