

DEVELOPMENT AND UTILIZATION OF URBAN SPECTRAL LIBRARY FOR REMOTE SENSING OF URBAN ENVIRONMENT

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Received 30 April 2011; received in revised form 11 June 2011; accepted 30 June 2011

Abstract:

Hyperspectral technology is useful for urban studies due to its capability in examining detailed spectral characteristics of urban materials. This study aims to develop a spectral library of urban materials and demonstrate its application in remote sensing analysis of an urban environment. Field measurements were conducted by using ASD FieldSpec 3 Spectroradiometer with wavelength range from 350 to 2500 nm. The spectral reflectance curves of urban materials were interpreted and analyzed. A collection of 22 spectral data was compiled into a spectral library. The spectral library was put to practical use by utilizing the reference spectra for WorldView-2 satellite image classification which demonstrates the usability of such infrastructure to facilitate further progress of remote sensing applications in Malaysia.

Keywords: Hyperspectral; Urban Materials; Spectral Library; Image Classification

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INTRODUCTION

In general, urban areas can be termed as developed areas, characterized primarily by the highest population density as well as distinguishable compared to its surrounding by the finest degree of man-made features. Meanwhile, urban materials consist of man-made materials (such as roofs and roads) and non built-up surfaces for instance vegetations, soils, rocks and water bodies.

Modern technological advancement has witnessed the wide application of hyperspectral remote sensing (HRS) in various fields of engineering for either observation or identification of urban materials' characteristics. HRS technology is useful for urban studies due to its capability to demonstrate high potential in examining the characteristics or properties of urban materials. Furthermore, HRS also provides numerous spectral details from its reflectance spectrum.

Urban environment can be considered as one of the most challenging areas to perform remote sensing analysis. This is due to its high spatial and spectral variety of surface materials. Further complication is attributed to the fact that urban environment is characterized by typical land cover surface together with existence of different types of materials (Herold *et al.*, 2003). In Malaysia's scope of engineering scenario, urban material study using HRS is yet to be explored intensively.

Common studies regarding the characteristic of reflectance or spectral signatures are usually dependent upon spectral libraries. These libraries contain pure spectral samples of surfaces. Such contents include wide range of materials over a continuum of higher spectral detail of wavelength range along with other information and documentation regarding the surface characteristics and the quality of the spectra (Herold and Roberts, 2010). The aforementioned spectral samples of surface materials can be derived from the hyperspectral remote

sensing observations together with field or laboratory spectral measurement. In this particular study, all the data of spectral signatures of urban materials were compiled into a web-based spectral library application known as UPMSpeclib.

METHODOLOGY

Study area

This study focused on a specific region in the urban area of Universiti Putra Malaysia's (UPM) main campus (Fig. 1). It is located approximately 23 km south of Kuala Lumpur and 16 km north of Putrajaya with latitude N 1° 24' to N 2° 32' and Longitude E 102° 42' to E 103° 38'. UPM campus area covers about 1,214 ha and 121 ha are allocated for administration buildings, faculties, lecture hall, student's dormitories, staff housing and recreation field. The study area mentioned is characterized by a mixture of urban land cover types and surface materials including various categories of roof and road types of different age and conditions.

Creation of comprehensive ground truth data

Classification process is necessary to initiate the pre-processing stage. It is taken followed by execution of the comprehensive ground truth data and the region of interest (ROI) by using ENVI software (ITTVIS, 2010). The classification process is meant for determining the types of urban materials for roofing, road and vegetation in the area concerned. It is deduced from the observation that the urban materials can be classified into two categories; man-made materials and non built-up surfaces (Table 1). Furthermore, seven types of roof materials, two types of road materials were ascertained to be of man-made materials. Meanwhile, two major types of trees, grass and soil were considered to be of non built-up surfaces category.

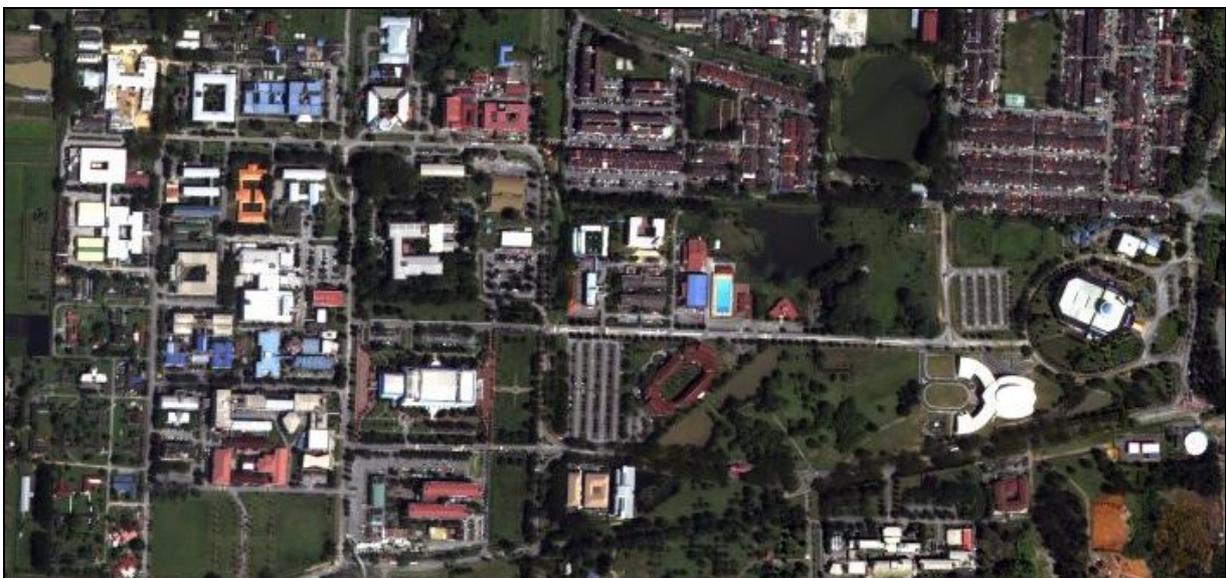


Fig. 1 Satellite image of the study area.

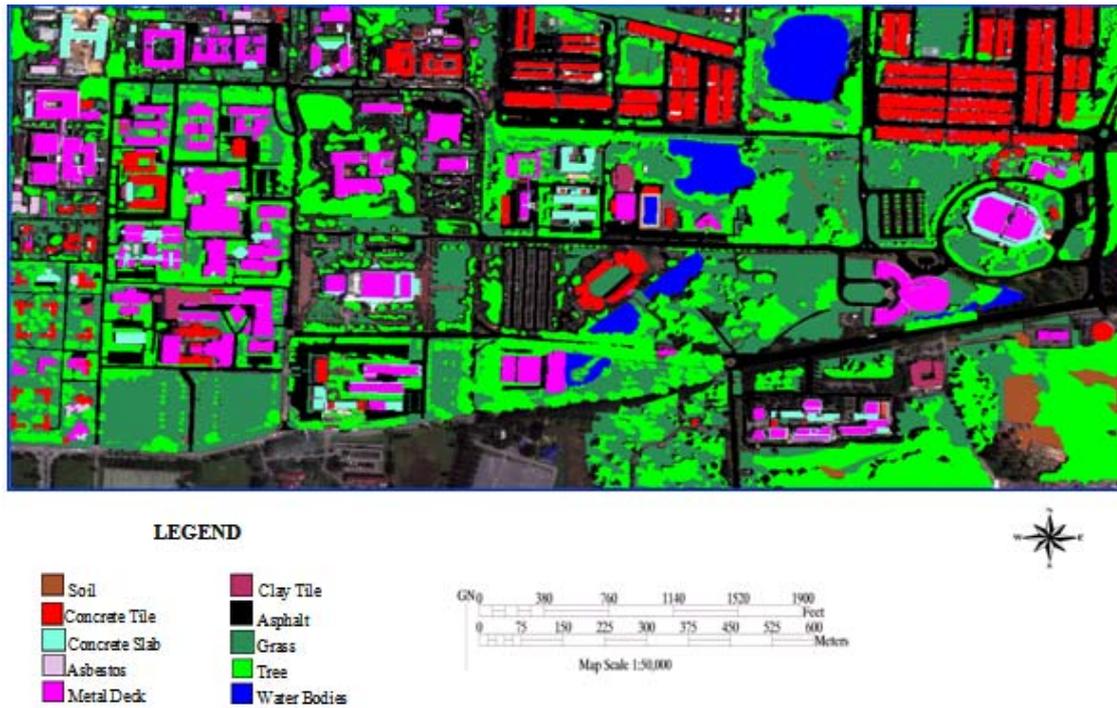


Fig. 2 Ground truth data.

Table 1. Classification of urban materials

Urban Materials		Types
Man-made materials	Roofing	Clay Tile Concrete Tile Metal Deck Asbestos Concrete Slab Polycarbonate Zinc
	Road	Asphalt Interlocking Block
Non built-up surfaces	Vegetation	<i>Samanea Saman</i> (Tree) <i>Roystonea Regina</i> (Tree) Grass
	Soil	

Performance of the classifiers was tested after the comprehensive ground truth data were available. The procedure involved recording of the coordinate data for every classified urban materials by using the handheld Global Positioning System (GPS) device. By using the ENVI 4.7 software, the Region of Interest (ROI) for urban materials was created (Fig. 2). Based on the ROIs, satellite image obtained from WorldView-2 satellite system was used for further classification process.

Instrumentation and software

Analytical Spectral Devices (ASD) FieldSpec 3 Spectroradiometer acts as a primary tool for spectral data acquisition (ASD, 2005). It is a general-purpose instrument with proven efficiency of application in various areas which require measurement of reflectance, transmittance, radiance, or irradiance. Moreover, it was specifically designed for field environmental remote sensing to acquire visible near infrared (VNIR) and short-wave infrared (SWIR) spectra. FieldSpec 3 Spectroradiometer is a compact and field portable device of incredible precision, with a spectral range of 350 nm to 2500 nm. It also has impressively rapid data collection time of 0.1 second per spectrum. In addition, FieldSpec 3 Spectroradiometer also allows for various subsections of the spectral range. While its most highly regarded features are in terms of performance and field-portability, this device also works well in the laboratory (ASD, 2005).

Essential software used in this study includes RS³, ViewSpec Pro Version 6.0, Microsoft Excel 2007 and ENVI 4.7. RS³ software refers to the third version of the Analytical Spectral Devices application. Its purpose is to receive and store the spectral data transmitted from ASD Spectroradiometer. ViewSpec Pro Version 6.0 software is a tool which performs the conversion process of spectra data and save them in .asd format. This software will then convert the .asd format into ASCII file of .txt format. Microsoft Excel 2007 subsequently translates the output data attained by conversion process into a graph. Meanwhile, ENVI 4.7 software is the ideal software for visualization, analysis

and presentation of all types of digital imagery. This software will then be used to perform an image classification for WorldView-2 images.

Spectral measurement

The spectral reflectance data were captured using an ASD FieldSpec 3 Spectroradiometer with the wavelength range of 350 nm to 2500 nm. Those measurements were carried out in the laboratory of Malaysian Remote Sensing Agency (ARSM) using samples of building materials identified in the UPM field site.

Spectral data were acquired in a set of five for each target material and the results were then averaged to find the final spectral reflectance value. Before recording the target's spectra, two types of radiant spectrum were recorded. These include the Dark Current (DC) and White References. Furthermore, the room must be covered appropriately to achieve complete darkness. When recording the target's spectra, some precautions were taken in order to increase the accuracy of the spectral data. The leaves were placed above the black paper in order to control the reflectance from spreading, which might possibly affect the target's spectrum.

Data processing

The spectral data, in which previously transmitted from ASD Spectroradiometer were received and stored using RS³ software in *.asd* format. The spectral data can then be viewed with Microsoft Excel after necessary conversion from *.asd* format to ASCII in *.txt* format. This is due to the format of spectral data received from ASD Spectroradiometer being incompatible with Microsoft Excel.

The ViewSpec Pro Version 6.0 software was utilized for the conversion process. All the spectral data save in *.asd* format were transferred to ASCII and later saved as *.txt* format (notepad files). Following the conversion process, the notepad file (*.txt*) which contains of those spectral data can be examined with Microsoft Excel software.

Furthermore, the data arrangement process was carried out using Microsoft Excel 2007 to average all the spectra data obtained from ASD Spectroradiometer device. The graph for all the urban materials of spectral reflectance was subsequently plotted. Then, the average data for each sample were saved in notepad and being employed later for compiling spectral data into web-based spectral library of UPMSpeclib.

Compilation into UPMSpeclib

All the collected spectral data were compiled into the web-based spectral library known as UPMSpeclib. This particular system offers management, analysis, and easy searching of spectral data by visual interface.

Image classification

Remote sensing data used for the image classification process is a WorldView-2 imagery acquired in 2009. The WorldView-2 is a new generation remote sensing satellite system, launched on 8th October 2009 and is the first high-resolution, eight-band, multispectral commercial satellite. It collects multispectral imagery at 1.8 meter resolution and panchromatic imagery at 0.46 meters. The spatial resolution of this image is 0.5 to 1 meter. This data set was selected for this study as it provides a high detailed imagery for precise map creation, change detection and in-depth image analysis. Furthermore, it covers a wide range of surface materials at a fine enough spatial resolution to be used in urban areas.

The collected spectral data acquired from a spectroradiometer can also be used in image classification process. In this study, one of the practical applications in image classification was demonstrated by using spectral data as end-members spectra. Before the classification process was performed, the spectral library which contains 22 reference spectra was developed using spectral library builder of ENVI 4.7 image processing software. Furthermore, the spectral library was spectrally resampled to similar wavebands of WorldView-2 image for further classification process. Besides, the masking process was performed to create the image masks for water bodies since the spectral data acquired did not include the water bodies' spectra.

Image classifications of urban materials have been carried out using Spectral Angle Mapper (SAM) and Maximum Likelihood (ML) algorithms. The SAM algorithm was chosen because it is an automated technique for a direct comparison image spectra to known spectra usually determined in a lab or field with a spectrometer or an end-members. The end-members spectra used by SAM can be from ASCII files or spectral libraries or extracted directly from an image as ROI average or Z-profile spectra. Meanwhile, ML classification is a statistical decision criterion to assist in the classification of overlapping signatures in which pixels are assigned to the class of highest probability (ITTVIS, 2009).

The classified image is further used in clump and sieve classes analysis before the accuracy for classified imagery was calculated. Clump and sieve are used to generalize classification images. Sieve is usually run

first to remove the isolated pixels based on size threshold, then clump is run to add spatial coherency to existing classes by combining adjacent similar classified areas (ITTVIS, 2009).

In addition, the accuracy for classified imagery has been evaluated by generating the confusion matrix by using the output of classified image from clump analysis as classification input file.

RESULTS

Spectral signatures of urban materials

The plotted graphs of urban materials are classified into two categories; man-made materials and non-built-up surfaces. The entire plotted graphs are acquired from previous processes by using Microsoft Excel 2007.

The man-made materials consisted of roof and road materials. The plotted graphs of man-made materials are represented as seven types of roof materials and two types of road materials.

Roof materials

The spectral profiles of roof materials obtained are also from different roof conditions due to aging process. They were categorized into new and old types of roof materials. **Figure 3a** shows new and older types of spectral reflectance of asbestos which are increasing at visible to SWIR regions. The spectral signatures of these two types of materials are similar except in the visible region. The spectral signature of old type of asbestos shows low absorption in the visible region. This is due to the mixture of original material and presence of algae.

The reflectance signatures for both materials look similar to each other with increased reflectance at longer wavelength and a reflectance peak in SWIR region as shown in **Fig. 3b**. New clay tile has the lowest reflectance compared to reflectance of older type and there is a strong absorption occurred at visible region for those two materials near 550 nm. According to Heiden *et al* (2001), liquid water and hydroxyl absorption typically found in clays, are lacking in fired brick and the reflectance is higher towards longer wavelengths due to loss of water in the production firing process.

Figure 3c shows spectral signatures of new and older types of concrete tile which are conspicuously different between each other. The reflectance of old type of concrete tile is high with the increasing reflectance toward longer wavelength. Meanwhile, for new type of clay tile, the peak reflectance occurred at NIR region and its reflectance signature is slightly low. The reflectance signature of this material is at its lowest due to its surface coating in dark grey colour. This

shows that dark objects absorb more electromagnetic radiation rather than reflecting it back and gives a low reflectance signature.

Figure 3d shows spectral signature of concrete slab which is covered by paint in white colour. Comparison of this concrete slab to spectra of typical fresh white paints claimed by Roberts and Herold (2004) demonstrates similarities in the spectral signature. Besides that, it can be seen that the broad absorption occurred along the SWIR regions.

Furthermore, **Fig. 3e** shows the spectral reflectance of metal deck roofing. The reflectance of new metal deck which is moderately dark blue colour is comparatively high within the NIR and SWIR regions. It shows the lowest reflectance of spectral signature for these two materials at 500 to 850 nm. Meanwhile, the reflectance of older metal deck roofing shows an inclined pattern towards the SWIR region.

Figure 3f shows the spectral reflectance of zinc. From the spectral signature above, it indicates the strong visible light absorption at 550 nm. The spectral reflectance also shows the increasing pattern along the SWIR regions. **Figure 3g** shows the spectra acquired from various types of polycarbonates. New types of polycarbonate with smooth and rough surfaces showed an increasing reflectance at longer wavelength and a reflectance peak occurs in the SWIR region. In addition, the reflectance of other materials is comparatively low. Furthermore, all materials show a prominent absorption feature which occur around 1650 nm in SWIR region. The low reflectance on these materials is due to its transparency characteristic. This is probably because some of the electromagnetic radiation that had penetrated through the material was absorbed by the black paper under the materials during spectral measurement.

Road materials

Herold *et al* (2004) had affirmed that an asphalt road represents an aggregate of crushed stones and various chemical components of tar or oil and also other hydrocarbons. **Figure 3h** presents the spectra of road materials of asphalt and interlocking block. The materials condition of interlocking block is due to the impact of aging process. The general spectral signatures of asphalt showed an increasing reflectance at longer wavelength and reflectance peak in the SWIR region. Furthermore, the asphalt spectrum has a minor absorption near 1850 nm and 2350 nm. Older type of interlocking block showed the highest reflectance among others at 850 nm. Besides, its spectral reflectance also look similar with new type of interlocking block with the peak reflectance occurred at 850 nm.

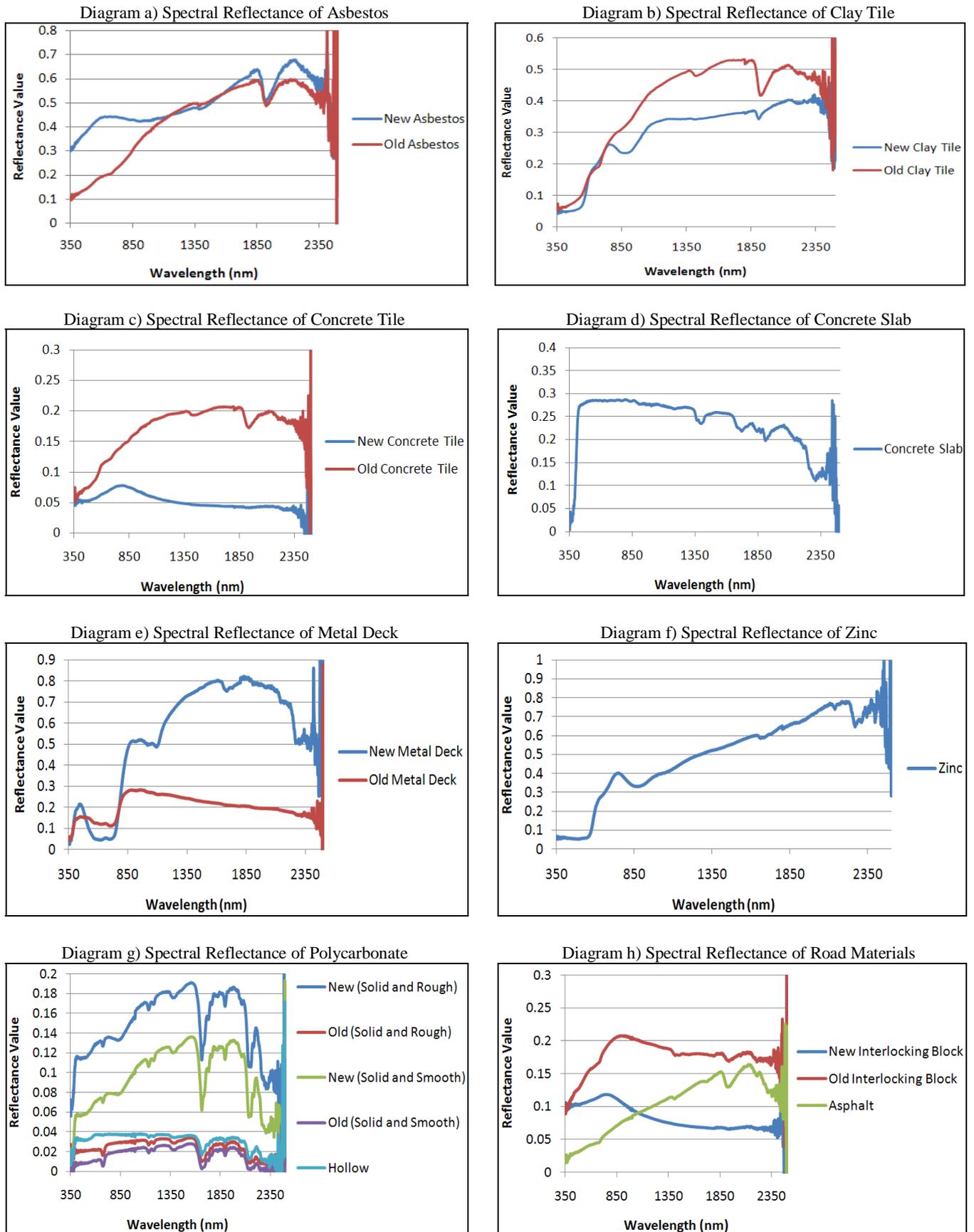


Fig. 3 Spectral reflectance for man-made materials; roof materials and road materials.

Non built-up surfaces

Figures 4a–4b shows the spectral reflectance from non built-up urban surfaces, which are vegetations and soil. **Figure 4a** shows the spectral characteristic of two types of plants namely *Samanea Saman* and *Roystonea Regia*. These plants are the major types of plant that exists at the main campus of UPM area. The graph shows the spectral reflectance for the healthy vegetation in which the reflectance peak is in green spectrum at 550 nm, minima at blue and red regions due to chlorophyll absorption. In the NIR region, the reflectance is high, however in SWIR region the reflectance is decreased.

Reflectance and emittance behaviour of an object, such as soil is highly dependent on its biochemical and physical fabric. From the **Fig. 4b**, it is shown only the general increase in reflectance from visible to SWIR region. The peak reflectance of soil spectra occurred near 1350 nm at NIR region and at 1750 nm at SWIR region. Furthermore, the minor absorption features appear maybe from contamination in the soil which occurred at 1850 nm.

Diagram a) Spectral Reflectance of Vegetation

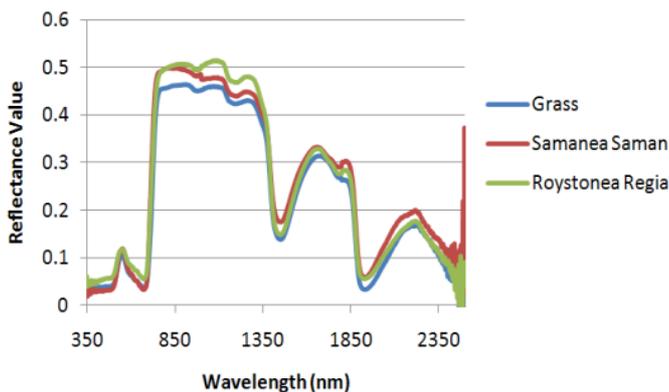


Fig. 4a Spectral reflectance for non-built-up1 surfaces; vegetation.

Diagram b) Spectral Reflectance of Soil

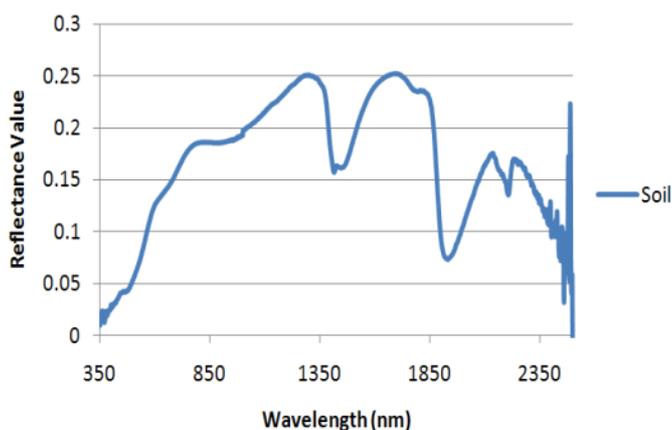


Fig. 4b Spectral reflectance for non-built-up surfaces; soil.

Compiling spectral data in UPMSpeclib

A spectral library consisting of 22 spectra had been compiled into a web-based UPM spectral library known as UPMSpeclib according to man-made and non-built up surface types. This system aims at collecting spectral data and corresponding background material parameters of different materials all over Malaysia.

In addition, this system consists of input data from spectral signatures and metadata which describe the characteristic of the spectral signatures. In this study, all the spectral data acquired are uploaded into UPM spectral library and the details of metadata are filled in accordance to the requirement needed.

One important parameter in the output stage in this system is the ability of the library to illustrate the spectral signature interactively. The interactive graph can combine up to two spectral signatures plot in a graph for comparing the reflectance value between two materials in the same category or class (Adam *et al.*, 2011). The full view of the results for the developed spectral library of urban materials can be acquired from web-based UPMSpeclib at www.upmspeclib.com.

Image classification

The WorldView-2 image was classified using SAM and ML algorithm with the use of reference spectral data from the spectral library and ROIs. A comparison of the resampled spectrum of each end-member and end-member pixel's spectrum from WorldView-2 data is shown in **Fig. 5**. Meanwhile, the resulting classified images are shown in **Fig. 6**. Furthermore, the accuracy of the classified imagery was evaluated by generating a confusion matrix by using 8 spectral samples.

The classification results show inaccuracies for most classes as shown in the confusion matrix (**Tables 2–3**). The overall accuracy of the classified imagery using SAM is 31.20 % with Kappa coefficient 0.1584 while overall accuracy for Maximum Likelihood is 73.32 % with kappa coefficient 0.6642. **Table 4** shows the comparison of producer's and user's accuracies for both algorithms.

Resampled WorldView-2 Spectrum

WorldView-2 image spectrum

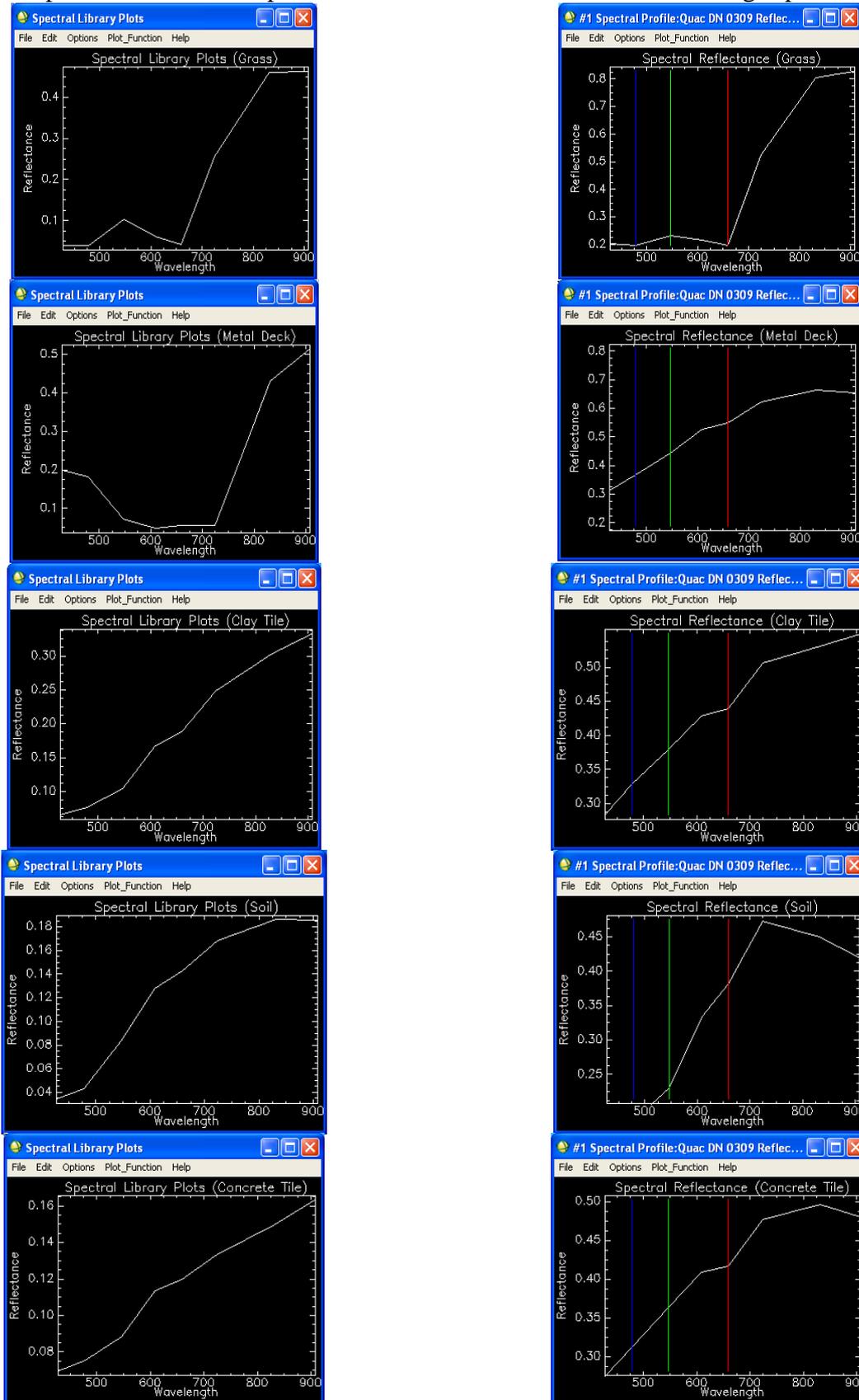


Fig. 5 A comparison of the resampled spectrum of each end-member and image spectrum from WorldView-2 data.

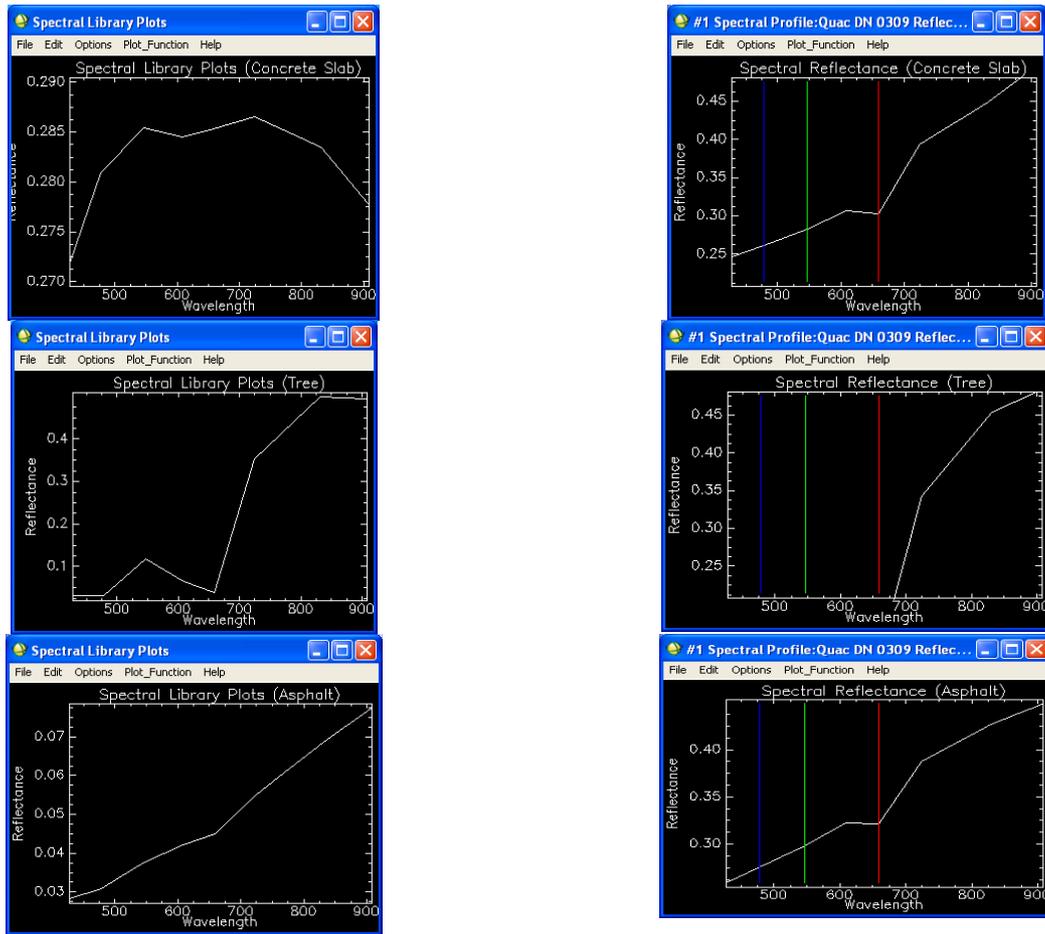


Fig. 5 (Cont.) A comparison of the resampled spectrum of each end-member and image spectrum from WorldView-2 data.

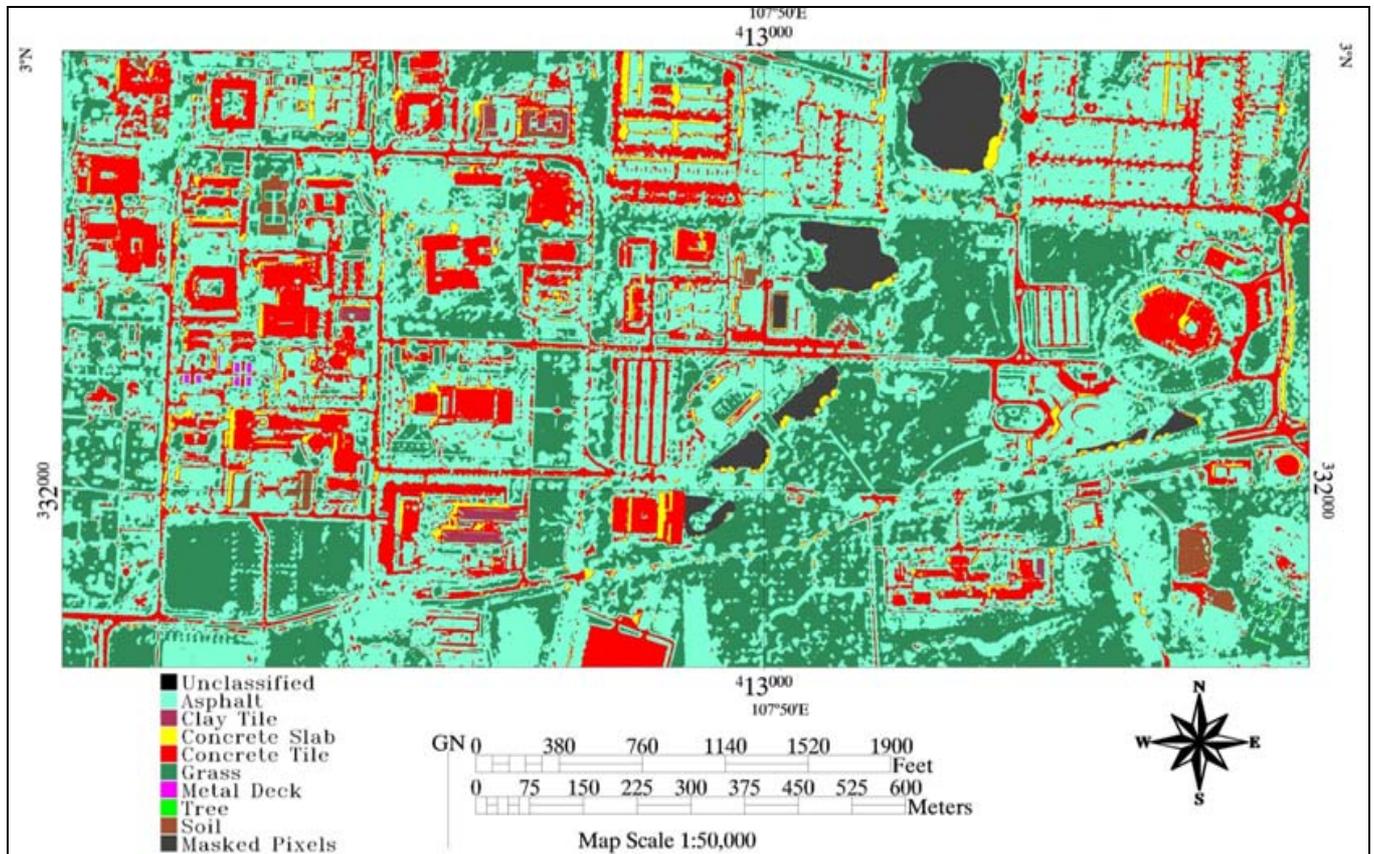


Fig. 6a Classified image by Spectral Angle Mapper (SAM) algorithm.

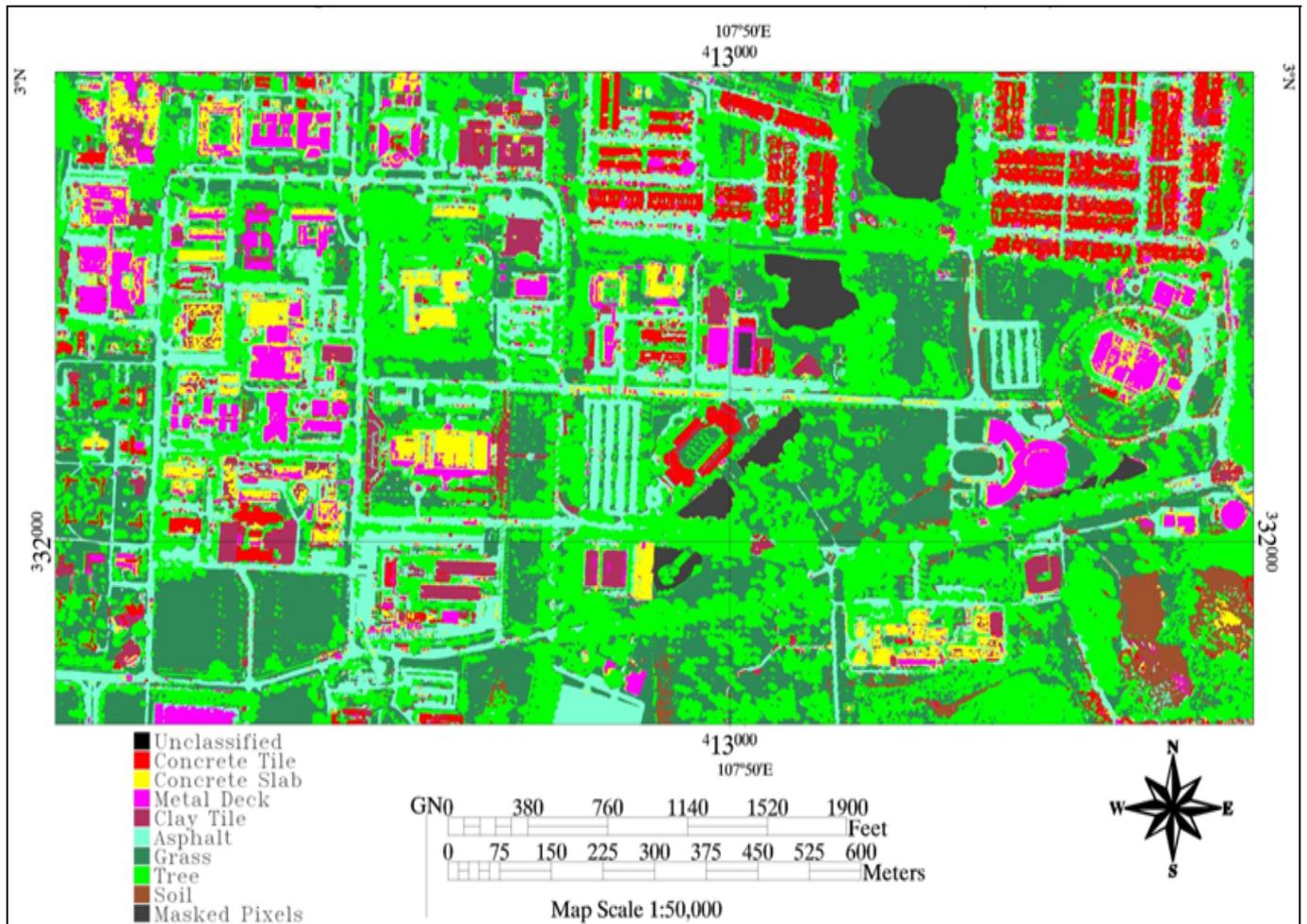


Fig. 6b Classified image by Maximum Likelihood (ML) algorithm.

Table 2. The confusion matrix results for SAM classification

Overall Accuracy = $(1336729/4284767)$ 31.1972%

Kappa Coefficient = 0.1584

Ground Truth (Percentage)

CLASS	Asphalt	Grass	Soil	Concrete Tile	Concrete Slab	Metal Deck	Clay Tile	Tree	Water Bodies	TOTAL
Unclassified	0.06	0.11	0.24	0.02	0.00	0.03	0.01	0.12	0.00	0.08
Asphalt	45.77	28.45	51.31	87.69	39.81	32.36	58.35	54.78	0.00	44.77
Grass	2.55	70.16	7.77	0.38	0.08	0.10	0.02	41.14	0.00	30.71
Soil	0.00	0.00	34.00	1.92	0.11	5.09	9.64	0.00	0.00	1.05
Concrete Tile	49.28	0.90	6.55	8.37	57.59	58.54	29.47	2.34	0.00	18.42
Concrete Slab	2.27	0.24	0.00	0.31	2.31	0.94	1.24	1.24	0.00	1.06
Metal Deck	0.00	0.00	0.00	0.00	0.01	0.51	0.00	0.00	0.00	0.05
Clay Tile	0.01	0.00	0.03	1.31	0.09	2.43	1.25	0.00	0.00	0.35
Tree	0.05	0.06	0.11	0.00	0.00	0.00	0.03	0.30	0.00	0.12
Masked Pixels	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.07	100.00	3.39
TOTAL	100	100	100	100	100	100	100	100	100	100

Table 3. The confusion matrix results for Maximum Likelihood classification

Overall Accuracy = (3141683/4284767) 73.3221%
Kappa Coefficient = 0.6642
 Ground Truth (Percentage)

CLASS	Concrete Tile	Concrete Slab	Metal Deck	Clay Tile	Asphalt	Grass	Tree	Soil	Water Bodies	TOTAL
Unclassified	0.08	0.09	0.06	0.07	0.12	0.13	0.14	0.27	0.00	0.12
Concrete Tile	66.81	16.01	1.31	9.65	1.86	0.43	0.53	2.14	0.00	6.51
Concrete Slab	4.33	34.40	30.05	10.10	4.73	0.42	0.57	0.86	0.00	5.20
Metal Deck	2.80	9.06	46.16	2.57	1.74	0.18	0.13	1.45	0.00	5.20
Clay Tile	10.82	3.53	16.95	64.00	1.51	0.25	0.09	0.94	0.00	3.43
Asphalt	5.33	28.16	4.66	9.27	70.63	3.80	3.55	0.48	0.00	17.64
Grass	0.65	0.13	0.05	0.25	3.34	78.88	12.00	7.18	0.00	24.17
Tree	8.31	8.42	0.40	2.01	15.49	13.01	80.40	8.36	0.00	31.86
Soil	0.86	0.19	0.35	2.07	0.58	2.81	2.51	78.33	0.00	2.50
Masked Pixels	0.00	0.00	0.00	0.00	0.00	0.08	0.07	0.00	100.00	3.39
TOTAL	100	100	100	100	100	100	100	100	100	100

Table 4. Comparison of producer's and user's accuracies of SAM and Maximum Likelihood classifier for image classification (percentage)

Class	Spectral Angle Mapper		Class	Maximum Likelihood	
	Producer	User		Producer	User
	Accuracy	Accuracy		Accuracy	Accuracy
Concrete Tile	8.37	3.61	Concrete Tile	66.81	81.56
Concrete Slab	2.31	4.62	Concrete Slab	34.40	14.07
Metal Deck	0.51	99.37	Metal Deck	46.16	83.00
Clay Tile	1.25	2.86	Clay Tile	64.00	14.76
Asphalt	45.77	20.37	Asphalt	70.63	79.76
Grass	70.16	57.06	Grass	78.88	81.53
Tree	0.30	77.49	Tree	80.40	77.05
Soil	34.00	32.65	Soil	78.33	31.71
Masked Pixels	100.00	98.75	Masked Pixels	100.00	98.75

DISCUSSIONS

Spectral reflectance

The 22 spectral data obtained from the laboratory measurements show unique spectral signatures of various urban materials particularly for man-made materials. The spectral signatures of older roofing and roads materials are comparatively different from the new materials.

According to the plotted graph, it is indicated that some of the spectral reflectance for older materials give high or increasing reflectance and some are in low or decreasing reflectance compared to the new materials. The decrease in spectra reflectance most likely reveals the impact of dirt or dusts which accumulate on the materials' surfaces, hence leading to changes in their spectral signatures.

Furthermore, some of the roofs and road materials are also affected by the aging process. The condition of these materials might change in the surface colour, coating by algae and dirt due to the aging process. Herold *et al.*, (2004) outlined that man-made materials generate additional chemical absorption which is not readily found in natural materials. A good example is paint, which has no analogue in the natural world. Besides, they stated that the urban materials can also be altered by coating such as algae, dirt, and dust or rubber tire marks which are found on roads, bridges and road paints.

Development of spectral library

The spectral data for urban materials are compiled in the UPM web-based spectral library. UPM spectral library is a useful web-based system for sharing those acquired spectral data and its output throughout this research. In addition, the UPM spectral library is more user-friendly for the spectral community in helping to determine spectral data availability and to find out about the owner of the data.

The development of spectral library will provide further benefits to other users. Diverse applications are possible by using the developed spectral library such as in image processing for urban mapping. As an example in urban surface materials mapping, the result obtained can be used for further implementation in many analyses such as roof types for energy conservation and fire danger assessment and impervious surfaces for improved estimation of flood potential and urban source pollution (Roberts and Herold, 2004). Moreover, the spectral data from spectral library can be used in classification algorithms or statistical classifiers technique such as Spectral Angle Mapper (SAM), Parallelepiped and Maximum Likelihood classifiers. These algorithms use spectral data as reference data for identifying classes from both multispectral and hyperspectral images.

The spectral library allows the users in management of input spectral dataset and metadata, online viewing of database content, online visualization of spectra, and downloading of spectral data and metadata. **Figure 7** below shows the user interface for managing the input spectral dataset in UPM spectral library.

The screenshot displays the 'UPM SPECTLIB' web interface. On the left, there is a navigation menu with icons for 'Manage Data', 'Analyze Data', 'Search Data', 'Equipment', 'Update Profile', and 'Logout'. The main area is titled 'Data' and contains a form for adding or editing spectral data. The form fields are as follows:

- Name:
- Category:
- Class:
- Subclass:
- Spectroradiometer: [Click here to add/edit](#)
- Location:
- Longitude:
- Latitude:
- State:
- District:
- Personnel: (automated)

Fig. 7 User interface in managing the spectral dataset.

In addition, the content creation for the spectral library needs to be well structured and managed. This will make the users to have an easy access in terms of search, retrieval and viewing information for the spectral data. The users may be able to search the data needed by different methods such as by category including class and subclass or by keying in the keywords. Besides, it will facilitate users to retrieve the information of the data stored. The spectral library also gives a collaboration potential in user applications study such as in forest management, agricultural commodities, astronomical and also in mineral exploration.

Classified image

Tables 2–3 shows the result of accuracy assessment for classified images using SAM algorithm and ML with 31.20 % and 73.32 % respectively. It shows that the image classification by using SAM algorithm gives a lower accuracy. This could be due to the use of end-members from the spectral library in the SAM algorithm contains more spectral matching errors compared to Maximum Likelihood algorithm which uses ROIs obtained from the image. Furthermore, it shows that the end-members from spectral library from hyperspectral measurements are not suitable for direct use in multispectral image data classification. More caution will be required in the resampling process in order to maintain similar spectral characteristics.

CONCLUSIONS AND RECOMMENDATIONS

A comprehensive collection of spectral reflectance from a variety of urban materials was acquired from laboratory measurements with the ASD Spectroradiometer device. The data were then compiled into a UPM spectral library. Based on this study, it can be concluded that the spectral reflectance of the urban materials in a specific wavelength range possess valuable information about the materials. This system provides a platform for the sharing of findings and spectral data and is also freely accessible for public use.

The application of the spectral library is not just restricted on providing the reference spectra for validation and visualization, but can also be used as input (end-members) for remote sensing image classification. The use of the reference spectral library data in classification of WorldView-2 multispectral satellite image yields an accuracy of 31.20 % using SAM and 73.32 % using Maximum Likelihood. The low accuracies are mainly due to the inadequacy of the 8 bands data to classify man-made materials (eg. the roof types) accurately.

Further study could utilize a fused airborne and spaceborne hyperspectral data which might improve classification accuracy of the complex urban environment. Object-oriented classification could be utilized to improve classification accuracy of the WorldView-2 data compared to the current pixel-based approach.

Acknowledgment Thanks are due to research officers of ARSM (Malaysian Remote Sensing

Agency), who were willing to conduct the ASD Spectroradiometer measurement and Mr. Zuraimi Suleiman who gave the permission in providing the equipment for this project. The authors acknowledge with thanks the helpful and constructive comments of the anonymous reviewers, which greatly aided the improvement of the paper.

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