UNIVERSITI PUTRA MALAYSIA

SPECTRAL DISCRIMINATION AND INDEX DEVELOPMENT OF ROOFING MATERIALS AND CONDITIONS USING FIELD SPECTROSCOPY AND WORLDVIEW-3 SATELLITE IMAGE

SARAH HANIM BINTI SAMSUDIN

FK 2016 63

SPECTRAL DISCRIMINATION AND INDEX DEVELOPMENT OF ROOFING MATERIALS AND CONDITIONS USING FIELD SPECTROSCOPY AND WORLDVIEW-3 SATELLITE IMAGE

By

SARAH HANIM BINTI SAMSUDIN

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Master of Science

June 2016

© COPYRIGHT UPM

COPYRIGHT

All material contained within the thesis, including without limitation text, logos, icon, photographs and all other artwork, is copyright material of Universiti Putra Malaysia unless otherwise stated. Use may be made of any material contained within the thesis for non-commercial purposes from the copyright holder. Commercial use of any material may only be made with the express, prior, written permission of Universiti Putra Malaysia.

Copyright © Universiti Putra Malaysia

© COPYRIGHT UPM

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Master of Science

SPECTRAL DISCRIMINATION AND INDEX DEVELOPMENT OF ROOFING MATERIALS AND CONDITIONS USING FIELD SPECTROSCOPY AND WORLDVIEW-3 SATELLITE IMAGE

By

SARAH HANIM BINTI SAMSUDIN

June 2016

Chairman: Assoc. Prof. Helmi Zulhaidi Mohd Shafri, PhD

Faculty: Engineering

Monitoring roofing materials and conditions are important to improve urban management and support the well-being of an urban environment. However, it is difficult to map the within-class roofing surfaces in the heterogeneous urban environment using multispectral remotely sensed data due to a wide-range of materials exist. Furthermore, restriction in multispectral bands has led to spectral confusions when mapping the within-class roofing types. Normal supervised pixel-based classification scheme is often applied to map urban land use and land cover which the accuracy is dependent on the training site information. Hence, the development of new approach is indispensable to improve the within-class roofing materials mapping. A technique combining the information of spectral and spatial characteristic could be considered as an effective way to improve urban analysis and overcome issues of limited spectral band and coarse spatial resolution of remote sensing data. Therefore, this study utilize the combination of field spectroscopy hyperspectral data and very high resolution multispectral data of WorldView-3 (WV-3) to map the roofing materials and conditions.

Hyperspectral data has the ability of providing adequate spectral information for discriminating within-class of roofing materials and conditions. This study utilizes field spectroscopy data as fundamental on analysing roofing spectral signature instead of using airborne hyperspectral data due to the expensive cost of data acquisition. However, handling hyperspectral data required effective method to reduce redundancy of data, yet maintaining the useful information. This research investigates a feature selection technique to discriminate between four different types of roof materials (i.e.: asbestos, concrete, clay and metal) and their conditions by using field spectroscopy within the range of 350 nm – 2500. Three feature selection algorithms of Genetic Algorithm (GA), Support Vector Machine (SVM) and Random Forest (RF) were used to select the most significant wavelengths since the algorithms works well with large size of data and widely applied for feature selection of hyperspectral remote sensing data. Results from feature selection

© COPYRIGHT UPM

specify that visible, Shortwave Infrared-1 (SWIR-1) and SWIR-2 (SWIR-2) spectral regions are important for roof materials and conditions separation. Comparatively, overall accuracy obtained from GA, SVM and RF algorithms are fairly high in percentage with GA and SVM both produced 96.3%, while RF yield 97.53% accuracy. Generally, the highest accuracy is produced using RF feature selection (97.53%), hence, describe the efficiency of RF algorithm for feature selection task using field spectroscopy data. Accuracy of spectra without feature selection was also investigated and the result was lower compared with classification using significant wavelengths. Result using all wavelengths mostly recorded 44.44%, while result using significant wavelengths mostly produced 100% accuracy. Therefore, the findings described the importance of selecting significant wavelengths to improve the spectral classification accuracy.

Additionally, new spectral indices of Normalized Difference Concrete Condition Index (NDCCI) and Normalized Difference Metal Condition Index (NDMCI) have been developed in this study for detecting concrete and metal roofing condition status. Significant wavelengths located at visible to near infrared spectral region were used as basis for developing spectral indices to be applied onto very high resolution satellite imagery of WV-3 satellite data. The classification accuracy using spectral indices were compared with the normal supervised pixel-based classification of SVM. Results show that the spectral indices produce higher accuracy compared to SVM classification with NDCCI produced 84.44% compared to SVM classification of concrete condition accuracy by 73.06%. NDMCI produced 94.17% accuracy which is higher compared to SVM classification of metal condition accuracy of 62.5%. Therefore, the results indicate that the application of the developed spectral indices is effective for mapping roofing conditions in the heterogeneous urban environment. Feasibility of the spectral indices developed were assessed by validating the indices on second study area, generating results of 72.06 for NDMCI and 70.3% accuracy for NDCCI. Lower accuracy obtained could be due to different study areas; the first study area is residential and commercial area, meanwhile the second study area is university area. Generally, both spectral indices could be considered for roofing materials and conditions detection application, however NDMCI perform better than NDCCI.

Generally, the findings of this study describes the importance of applying feature selection as a preliminary process before developing a spectral index to eliminate uninformative data and enhance the separation between impervious surfaces. Spectral index of NDCCI and NDMCI found to be effective in providing roof degradation status map in effective time-manner and parameter-free algorithm compared to normal supervised classification scheme. However, the proposed technique has some limitations which the classification is depended on roof brightness, hence, lead to misclassification between new metal roofs and new concrete roofs. This approach also required removal of natural land cover such as vegetation and water bodies to provide better delineation of impervious surfaces. Therefore, further improvement is needed to provide better classification accuracy for delineation of roofing types. The output from this study could contribute into new insight of urban planning and monitoring and sensor development for urban mapping.

© COPYRIGHT UPM

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Master Sains

DISKRIMINASI SPEKTRUM DAN PEMBINAAN INDEKS UNTUK JENIS DAN KEADAAN BUMBUNG MENGGUNAKAN SPEKTROSKOPI LAPANGAN DAN DATA SATELIT WORLDVIEW-3

Oleh

SARAH HANIM BINTI SAMSUDIN

Jun 2016

Pengerusi: Professor Madya Helmi Zulhaidi Mohd Shafri, PhD

Fakuti: Kejuruteraan

Pemantauan bahan dan keadaan bumbung adalah penting untuk meningkatkan pengurusan bandar dan membantu dalam memastikan kesejahteraan kawasan persekitaran bandar. Walau bagaimanapun, memetakan antara kelas permukaan berbumbung dalam persekitaran bandar yang heterogen menggunakan data penderiaan jauh adalah rumit kerana kepelbagaian bahan yang wujud. Tambahan pula, limitasi jalur spectrum data multispectral telah menyebabkan kekeliruan spektrum apabila pemetaan antara kelas bahan dilakukan. Kaedah klasifikasi diselia normal berasaskan piksel sering digunakan untuk memetakan kawasan guna tanah bandar. Walaubagaimanapun, ketepatan menggunakan kaedah klasifikasi ini adalah bergantung kepada maklumat tapak latihan yang disediakan. Oleh itu, pembangunan teknik baru adalah amat diperlukan untuk meningkatkan pemetaan antara kelas bahan permukaan berumbung. Teknik yang menggabungkan maklumat ciri spektrum dan spatial boleh dianggap sebagai cara yang berkesan untuk meningkatkan analisis bandar dan mengatasi masalah-masalah data penderiaan jauh seperti jalur spektram yang terhad dan resolusi ruang kasar. Oleh itu, kajian ini menggunakan gabungan data hyperspectral spektroskopi lapangan dan imej satelit multispectral beresolusi yang sangat tinggi iaitu WorldView-3 (WV-3) untuk memetakan bahan bumbung dan keadaannya.

Data hyperspectral mempunyai keupayaan untuk menyediakan maklumat spektrum yang mencukupi untuk tujuan diskriminasi antara-kelas bahan bumbung dan keadaannya. Kajian ini menggunakan data spektroskopi lapangan sebagai asas untuk menganalisis karakter spectrum jenis-jenis bumbung, ini adalah kerana penggunaan data hyperspectral udara memerlukan kos yang mahal untuk proses pemerolehan data. Walau bagaimanapun, pengendalian data hyperspectral memerlukan kaedah yang berkesan untuk mengurangkan pertindihan data, tetapi masih mengekalkan maklumat yang berguna. Kajian ini menyiasat teknik pemilihan ciri untuk membezakan antara empat jenis bahan bumbung (iaitu: asbestos, konkrit, tanah liat dan logam) dan keadaan mereka dengan menggunakan alat spektroskopi lapangan dalam julat 350 nm - 2500. Tiga

© COPYRIGHT UPM

algoritma telah digunakan iaitu Genetic Algorithm (GA), Support Vector Machine (SVM) dan Random Forest (RF) untuk memilih panjang gelombang yang paling penting. Algoritma-algoritma ini digunakan kerana ianya mampu berfungsi dengan baik apabila mempunyai saiz data yang besar serta telah digunakan dengan meluas untuk pemilihan ciri data hyperspectral. Keputusan dari pemilihan ciri telah menentukan bahawa spectrum pada gelombang boleh nampak, gelombang infra merah pendek-1 (SWIR-1) dan gelombang infra merah pendek-2 (SWIR-2) adalah penting untuk membezakan bahan-bahan dan keadaan bumbung yang berlainan. Secara perbandingan, ketepatan keseluruhan yang diperolehi daripada algoritma GA, SVM dan RF adalah agak tinggi dengan peratusan menggunakan GA dan SVM adalah 96.3%, manakala RF menghasilkan ketepatan 97.53%. Oleh itu, keputusan menggunakan pemilihan ciri RF (97.53%) adalah yang paling tinggi, secara tidak langsung menggambarkan kecekapan algoritma RF untuk tugas pemilihan ciri menggunakan data spektroskopi lapangan. Ketepatan spektrum tanpa pemilihan ciri turut disiasat dan hasilnya adalah lebih rendah berbanding dengan klasifikasi menggunakan panjang gelombang yang penting. Keputusan menggunakan semua panjang gelombang kebanyakannya mencatatkan 44.44%, manakala hasil menggunakan panjang gelombang yang penting kebanyakannya menghasilkan ketepatan 100%. Oleh itu, dapatan daripada kajian ini menunjukkan kepentingan memilih panjang gelombang yang penting untuk meningkatkan klasifikasi ketepatan spektrum.

Di dalam kajian ini, indeks spektrum baru iaitu 'Normalized Difference Concrete Condition Index' (NDCCI) dan 'Normalized Difference Metal Condition Index' (NDMCI) telah dibangunkan untuk mengesan status keadaan bumbung konkrit dan keadaan bumbung logam. Panjang gelombang penting yang terletak di kawasan spektrum boleh nampak digunakan sebagai asas untuk membangunkan indeks spektrum yang akan digunakan ke imej satelit WV-3. Pengelasan ketepatan menggunakan indeks spektrum telah dibandingkan dengan klasifikasi berdasarkan piksel-diselia biasa, iaitu SVM. Keputusan menunjukkan bahawa klasiikasi mengunkan indeks spektrum menghasilkan ketepatan yang lebih tinggi berbanding klasifikasi menggunakan SVM dengan NDCCI dihasilkan 84.44% berbanding klasifikasi SVM keadaan ketepatan konkrit sebanyak 73.06%. NDMCI pula menghasilkan ketepatan 94.17% iaitu lebih tinggi berbanding klasifikasi SVM dengan 62.5%. Oleh itu, keputusan menunjukkan bahawa penggunaan indeks spektrum adalah berkesan untuk pemetaan keadaan permukaan bumbung di kawasan bandar yang heterogen. Ujian pengesahihan telah dijalankan di kawasan kajian yang berbeza menggunakan indeks spektrum yang dibangunkan untuk menilai keupayaan indeks menghasilkan peta status keadaan permukaan bumbung. NDMCI telah menjana ketepatan sebanyak 72.06%, manakal NDCCI menghasilkan ketepatan sebanyak 70.3%. Ketepatan yang lebih rendah diperolehi mungkin disebabkan kawasan kajian yang berbeza; kawasan kajian yang pertama adalah kawasan perumahan dan komersil, sementara itu kawasan kajian yang kedua ialah kawasan universiti. Secara umumnya, kedua-dua indeks spektrum boleh dipertimbangkan untuk pemetaan bahan bumbung dan keadaannya, bagaimanapun prestasi NDMCI adalah lebih baik daripada NDCCI.

Secara umumnya, hasil kajian ini telah menggambarkan kepentingan mengaplikasi pemilihan ciri sebagai proses awal sebelum membangunkan indeks spektrum untuk menghapuskan data tidak bermaklumat dan meningkatkan pemisahan antara permukaan kedap. Selain itu, indeks spectrum NDCCI dan NDMCI juga didapati berkesan dalam menyediakan peta status degradasi bumbung dengan lebin cepat dan efektif kerana menggunakan indeks yang bebas dari parameter berbanding kaedah klasifikasi diselia

© COPYRIGHT UPM

yang normal. Walau bagaimanapun, teknik yang dicadangkan mempunyai beberapa batasan seperti terpengaruh dengan kecerahan permukaan bumbung. Salah pengelasan juga cenderung terjadi antara bumbung logam baru dan bumbung konkrit baru. Tambahan pula, teknik spectrum indeks ini memerlukan penyingkiran kawasan guna tanah semula jadi seperti tumbuh-tumbuhan dan badan air untuk membezakan permukaan kedap dengan lebih berkesan. Oleh itu, penambahbaikan diperlukan untuk menyediakan klasifikasi perbezaan jenis-jenis bumbing dengan ketepatan yang lebih baik pada masa hadapan. Hasil dapatan daripada kajian ini boleh menyumbang kepada pengetahuan baru dalam bidang perancangan dan pemantauan bandar serta pembangunan sensor untuk pemetaan bandar.

© COPYRIGHT UPM

ACKNOWLEDGEMENTS

First of all, thanks to Allah for His grace and blessing that give me strength in accomplishing my research study in Master Science (Remote Sensing). Highest gratitude to the lecturers especially to my supervisor Assoc. Prof. Dr. Helmi Zulhaidi for his guidance, time and attention in assisting me throughout my study in Universiti Putra Malaysia. Sincere appreciation to my co-supervisor, Prof. Dato' Dr. Shattri Bin Mansor for his guidance and advice. I would also like to thanks those who contribute to this study either directly or indirectly, especially to those who helps in the field data measurement and Izzuddin Anuar who has guided me in field spectroscopy data processing. Special thanks to Alireza Hamedianfar who has assist and contributing ideas to improve my study. I would also like to dedicate my gratitude to my great friends Maizatul Akma, Nik Mohd. Ramli, Mustafa Al-Habshi, Norshahniza, Ikhwan, Athirah, and Dr. Farrah Melissa who has accompanied, motivate and assist me during my study years in Universiti Putra Malaysia. Last but not least, I would like to express great thanks to my family for their continuous support and encouragement which has motivated me to accomplish this study.

© COPYRIGHT UPM

© COPYRIGHT UPM

This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Master of Science. The members of the Supervisory Committee were as follows:

Helmi Zulhaidi Mohd Shafri, PhD
Associate Professor
Faculty of Engineering
Universiti Putra Malaysia
(Chairman)

Shattri Bin Mansor, PhD
Professor
Faculty of Engineering
Universiti Putra Malaysia
(Member)

_____

BUJANG KIM HUAT, PhD
Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

Date:

© COPYRIGHT UPM

Declaration by graduate student

I hereby confirm that:

- this thesis is my original work;
- quotations, illustrations and citations have been duly referenced;
- this thesis has not been submitted previously or concurrently for any other degree at any other institutions;
- intellectual property from the thesis and copyright of thesis are fully-owned by Universiti Putra Malaysia, as according to the Universiti Putra Malaysia
- (Research) Rules 2012;
- written permission must be obtained from supervisor and the office of Deputy Vice-Chancellor (Research and Innovation) before thesis is published (in the form of written, printed or in electronic form) including books, journals, modules, proceedings, popular writings, seminar papers, manuscripts, posters, reports, lecture notes, learning modules or any other materials as stated in the Universiti Putra Malaysia (Research) Rules 2012;
- there is no plagiarism or data falsification/fabrication in the thesis, and scholarly integrity is upheld as according to the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) and the Universiti Putra Malaysia (Research) Rules 2012. The thesis has undergone plagiarism detection software.

Signature: _____ Date: _____

Name and Matric No.: _____

© COPYRIGHT UPM

Declaration by Members of Supervisory Committee

This is to confirm that:

- the research conducted and the writing of the thesis as under our supervision;
- supervision responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) are adhered to.

Signature:	_____	Signature	_____
Name of Chairman of Supervisory Committee:	_____	Name of Member of Supervisory Committee	_____

© COPYRIGHT UPM

TABLE OF CONTENTS

	Page
ABSTRACT	i
ABSTRAK	iii
ACKNOWLEDGEMENTS	vi
APPROVAL	vii
DECLARATION	ix
LIST OF TABLES	xiv
LIST OF FIGURES	xv
LIST OF ABBREVIATIONS	xvii
CHAPTER	
1 INTRODUCTION	
1.1 Background of study	1
1.2 Problem Statements	3
1.3 Significance of Study	4
1.4 Research Objectives	5
1.5 Scope of the Study	5
1.6 Research Gap	6
1.7 Thesis Organization	7
2 LITERATURE REVIEW	
2.1 Introduction	8
2.2 Introduction to Remote Sensing System	8
2.3 Hyperspectral Remote Sensing	10
2.4 Field Spectroscopy	12
2.5 Spectral Characteristic and Spectral Variability of Impervious Surfaces	13
2.6 Roof Materials in Malaysia	17
2.7 Remote Sensing Of Impervious Surfaces	18
2.7.1 Multispectral Remote Sensing Of Impervious Surfaces	18
2.7.2 Hyperspectral Remote Sensing Of Impervious Surfaces	20
2.8 Field Hyperspectral Data Interpretation	21
2.8.1 Data Denoising	22
2.8.2 Dimensionality Reduction	22
2.8.3 Feature Extraction	22
2.8.4 Feature Selection	23
2.8.4.1 SVM Feature Selection	24
2.8.4.2 RF Feature Selection	25
2.8.4.3 GA Feature Selection	26
2.8.5 Spectral classification	27
2.9 Index Development	28
2.10 Existing Impervious Surfaces Spectral Index	28
2.11 Summary	29

© COPYRIGHT UPM

3 METHODOLOGY
3.1 Introduction 31
3.2 Study Area and Data 32
3.3 Phase I - Field Spectroscopy Data Acquisition 33
3.3.1 Roofing Samples 33
3.3.2 ASD Fieldspec-3 Instrument 34
3.3.3 Field Data Collection 35
3.4 Phase II - Signal Processing 37
3.4.1 Pre-processing 37
3.4.1.1 Data Conversion 37
3.4.1.2 Noise Removal 37
3.4.1.3 Normalization 38
3.4.1.4 Training and Testing Set Development 38
3.4.2 Processing (Feature Selection) 39
3.4.2.1 SVM Feature Selection 40
3.4.2.2 RF Feature Selection 41
3.4.2.3 GA Feature Selection 42
3.4.3 Processing (Spectral Classification) 43
3.4.4 Post processing – Accuracy Assessment 44
3.5 Phase III - Spectral Indices Development 44
3.6 Phase IV - Application and Mapping 45
3.6.1 Pre-processing of WorldView-3 Satellite Data 46
3.6.2 Spectral Indices Application 46
3.6.3 Spectral Indices Classification 48
3.6.4 Accuracy Assessment and Validation 49
3.7 Summary 49

4 RESULTS AND DISCUSSIONS
4.1 Introduction 50
4.2 Phase I – Signal Pre-processing 50
4.2.1 Data Conversion 50
4.2.2 Noise Removal 50
4.2.3 Normalization 52
4.3 Spectral Characterization of Roofing Types 53
4.4 Phase II - Signal Processing 55
4.4.1 Feature Selection 55
4.4.1.1.SVM Feature Selection 55
4.4.1.2 RF Feature Selection 56
4.4.1.3 GA Feature Selection 58
4.4.1.4 Analysis of Feature Selection 59
4.4.2 Spectral Classification and Accuracy Assessment 59
4.4.3 Within-class Spectral Classification 61
4.5 Phase III – Spectral Indices Development 62
4.5.1 Development of Possible Band Ratio 62
4.5.2 Optimum Index Factor (OIF) 63
4.6 Phase IV – Spectral Indices Application 64
4.6.1 Spectral Indices of Concrete Roofing Condition 64
4.6.2 Spectral Indices of Metal Roofing Condition 66

© COPYRIGHT UPM

4.7 Support Vector Machine Classification (Supervised Spectral-based Classification) 68
4.8 Comparison of Spectral Indices Classification with Supervised Spectral-based Classification 69
4.9 Spectral Indices Validation 71
4.10 Discussions on NDCCI and NDMCI 73
4.11 Summary 75

5 CONCLUSIONS AND RECOMMENDATIONS
5.1 Introduction 76
5.2 Conclusions 76
5.2.1 Significant Wavelengths Selection 76
5.2.2 Comparative Analysis of Feature Selection Algorithms 76
5.2.3 Development of Spectral Indices 77
5.2 Limitation of Research 78
5.3 Recommendations for Future Works 78

REFERENCES 80
BIODATA OF STUDENT 97
LIST OF PUBLICATIONS 98

© COPYRIGHT UPM

LIST OF TABLES

Table		Page
3.1	Specification of Worldview-3 sensor	32
4.1	SVM feature selection for inter-class	56
4.2	SVM feature selection for intra-class	56
4.3	RF feature selection for inter-class	57
4.4	RF feature selection for intra-class	57
4.5	GA feature selection for inter-class	58
4.6	GA feature selection for intra-class	58
4.7	Classification accuracy for roof types and roof conditions classification using significant wavelengths produced from SVM, RF and GA model and all wavelengths	60
4.8	Confusion matrix of SVM (a), RF (b), and GA (c) for classifying roofing materials	61
4.9	Comparison of the OIF values for concrete roofing conditions detection	63
4.10	Comparison of the OIF values for metal roofing conditions detection	63
4.11	Index values for new concrete, weathered concrete and non-concrete impervious surfaces classes.	66
4.12	Index values for new metal, weathered metal and non-metal impervious surfaces classes.	67
4.13	Accuracy assessment of NDCCI and SVM classification for concrete roofing conditions.	70
4.14	Accuracy assessment of NDMCI and SVM classification for metal roofing conditions	70
4.15	Accuracy assessment of NDCCI and NDMCI validation	72

© COPYRIGHT UPM

LIST OF FIGURES

Figure		Page
2.1	(a) Passive remote sensing system, (b) Active remote sensing system	8
2.2	Spectral regions of electromagnetic spectrum	9
2.3	Comparisons of multispectral bands and hyperspectral bands	10
2.4	Hyperspectral remote sensing system	11
2.5	Spectroradiometer measurement system	13
2.6	(a) Spectral signature of roof surfaces; (b) Spectral signature of road surfaces	14
2.7	Spectral reflectance of (a) different conditions of asphalt, (b) different conditions of concrete road materials, (c) different types of roofing materials.	16
2.8	Spectral characterizations for roofing materials of (a) asbestos, (b) clay, (c) concrete and (d) polycarbonate	17
2.9	Roofing materials used for different housing types in Malaysia	18
2.10	General techniques of hyperspectral signal processing	21
3.1	General Research Methodology	31
3.2	Study Area	32
3.3	Roofing materials: (a) new metal; (b) weathered metal; (c) new asbestos; (d) weathered asbestos; (e) new clay; (f) weathered clay; (g) new concrete; and (h) weathered concrete	33
3.4	ASD Fieldspec 3 instrument	34
3.5	Measurement of spectralon during data acquisition	35
3.6	Position of sample and instrument during data acquisition	36
3.7	SVM –RFE workflow	40
3.8	GA feature selection workflow	42
3.9	Spectral indices development and application workflow	44
4.1	Spectra plot of (a) original spectra and (b) after noise removal	51
4.2	a) Spectra of roofing types before normalization and (b) Spectra of roofing types after normalization	52
4.3	Spectral signature of (a) asbestos roof types; (b) clay roof types; (c) concrete roof types; (d) metal roof types	54
4.4	NDCCI classification image	65
4.5	Histogram and class break for NDCCI classes.	65

© COPYRIGHT UPM

4.6	NDMCI classification image	67
4.7	Histogram and class break for NDMCI classes	67
4.8	SVM classification for (a) concrete roof material; (b) metal roof material.	68
4.9	Validation of NDCCI classification	71
4.10	Validation of NDCCI classification	72
4.11	Location of significant wavelengths for (a) concrete roofs; (b) metal roofs	74

© COPYRIGHT UPM

LIST OF ABBREVIATIONS

GA	Genetic Algorithm
SVM	Support Vector Machine
RF	Random Forest
NDCCI	Normalized Difference Concrete Condition Index
NDMCI	Normalized Difference Metal Condition Index
UAV	Unmanned Aerial Vehicle
VHR	Very High Resolution
NDVI	Normalized Difference Vegetation Index
GER	Geophysical Environmental Research
ASD	Analytical Spectral Device
PC	Personal Computer
SWIR	Shortwave Infrared
PE	Polyethylene
UHI	Urban Heat Island
LSMA	Linear Spectral Mixture Analysis
V-I-S	Vegetation-Impervious-Soil surfaces
MIVIS	Multispectral Infrared and Visible Imaging Spectrometer
RFE-SVM	Recursive Feature Elimination-Support Vector Machine
CFS	Correlation-based Feature Selection
mRMR	Minimum-Redundancy-Maximum-Relevance
EFS-SVM	Embedded Feature Selection-Support Vector Machine
MR-SVM	Modified Recursive-Support Vector Machine
TW-SVM	Twin-Support Vector Machine
NN	Neural Network
OOB	Out of Bag
DAIS	Digital Airborne Imaging Spectrometer
k-NN	k-Nearest Neighbour
REI	Road Extraction Index
NIR-2	Near Infrared-2
NDBI	Normalized Difference Built-up Index
BAEI	Built-up Area Extraction Index
NBAI	Normalized Built Up Area Index
BRBA	Band Ratio for Built-up Area
NDISI	Normalized Difference Impervious Surface Index
MNDISI	Modifies Normalized Difference Impervious Surface Index
ISD	Index of Surface Deterioration
WV-3	WorldView-3
SWIR-1	Shortwave Infrared-1
SWIR-2	Shortwave Infrared-1
VNIR	Visible-Near Infrared
WEKA	Waikato Environment for Knowledge Analysis
ENVI	Exelis Visual Information Solutions
DN	Digital Number
OIF	Optimum Index Factor
NDWI	Normalized Difference Water Index
WV-2	WorldView-2
OA	Overall Accuracy

© COPYRIGHT UPM

© COPYRIGHT UPM

CHAPTER 1

INTRODUCTION

1.1 Background of Study

The development of remote sensing technology has improved urban mapping tasks to provide essential information in urban monitoring and urban management. The motivation for improving within-class impervious surfaces mapping in urban area, arose from the worldwide demographic trends, indicating that half of the world's population is living in cities, and is expected to increase into future decades, causing changes in spatial distribution of global population (United Nation, 2014). Hence, one of the effects of rapid urbanization phenomenon is the transformation of land use in urban areas, since pervious surfaces will be transformed into impervious surfaces to provide better infrastructures for urban citizens (Miller et al., 2014).

Impervious surface mapping is essential in urban studies since it is considered a key indicator of anthropogenic impact upon the urban environment (Weng, 2012). The characteristics of impervious surfaces, which prevent infiltration of water into the ground, have consequential effects on urban hydrological systems and ecology (Simonovic, 2012; Chithra et al., 2015). Therefore, detection of roofing materials and conditions over an area is very important, as some of the roofing materials, such as asbestos-cement roofs, are harmful to human health (Frassy et al., 2014; Cilia et al., 2015). Besides, some of the roofing materials are constructed from non-reflective material, which releases a high amount of heat into the environment, thereby causes Urban Heat Island phenomenon (Yu and Lu, 2014; Li et al., 2014; Cilia et al., 2015).

Remote sensing has been introduced as an efficient tool to map roof surfaces at a large scale compared to the conventional method, which is through ground survey and manual inspection (Cilia et al., 2015; Swanson & Helmlinger, 2014). In the early usage of the remote sensing technology, identification of urban features was done by utilizing pixel-based supervised classification. However, heterogeneity of features and different surface materials available in urban environments has created a challenge in the urban remote sensing application to discriminate between land cover classes due to the wide range of materials used for manmade surfaces (Chisense, 2012; Taherzadeh and Shafri, 2013; Fiumi et al., 2012; Lu and Moran, 2010). Traditional supervised classification techniques often result in poor classification and a salt-and-pepper effect; this could be due to mixed land cover components in urban areas (Hamedianfar and Shafri, 2014). Apart from that, similarity in colour for certain types of roofs and similar spectral information (i.e.: clay roofs, steel roofs and road) also led to confusion when interpreting the impervious surfaces (Hamedianfar and Shafri, 2014; Herold et al., 2004; Taherzadeh and Shafri, 2013). Therefore, applying this technique required adequate information on the training site to classify the within-class of roofing types.

© COPYRIGHT UPM

Recently, knowledge of detecting within-class roofing types up to parcel level is required to improve inter-class and intra-class of urban classification. Therefore, very high resolution (VHR) satellite imagery, such as WorldView, IKONOS and Quickbird (Taherzadeh et al., 2014) is suitable to be used due to high spatial resolution specification. Although VHR could provide sufficient spatial resolution to extract detailed information of land cover, a suitable classification method is required to provide good classification accuracy, especially when classifying a high-spectral variety of urban land cover classes (Lu et al., 2010). Currently, object-based image analysis (OBIA) was introduced to be used with VHR imagery to improve the within-class roofing type's classification. OBIA technique has advantages of providing high accuracy classification for within-class detection and could differentiate roofing materials from other urban land covers (Hamedianfar and Shafri, 2015; Hamedianfar and Shafri, 2016). However, OBIA techniques involve complex processing and long computation time to produce classification results (McMahon, 2007; Deng and Wu, 2012). Apart from that, the limitation of spectral bands of multispectral imagery has also led to misclassification error when applying OBIA classification on VHR satellite imagery (Taherzadeh and Shafri, 2013; Hamedianfar and Shafri, 2014).

The introduction of hyperspectral technology in remote sensing has provided new insights in urban mapping, since it is equipped with hundreds and contiguous spectral bands that make it efficient for materials detection (Licciardi, 2014). The exploitation of this technology in urban environmental study is still being investigated for impervious surface materials characterization in current research (Taherzadeh and Shafri, 2013; Weng, 2012). Hyperspectral technology could be useful for inter-class material detection since roofing materials spectral are mostly influenced by material, aging and weathering factors (Lacherade et al., 2005). Thus, it has the advantage of supplying sufficient information to improve material and surface condition detection compared to multispectral data. Nevertheless, the abundance of hyperspectral data is highly correlated with each other and are redundant, which consequently leads to complexity of processing. Hence, selecting only suitable wavelengths or bands for discrimination of roofing material is vital to improve the urban materials classification (Weng, 2012; Le Bris et al., 2016).

Machine learning algorithms have recently been used as a tool to select suitable wavelengths discriminating between materials as well as reducing the redundancy of data (Pal, 2010; Kumar and Minz, 2014). Although there are many machine learning algorithms that are developed for feature selection tasks, the most common algorithms used for hyperspectral remote sensing are the Genetic Algorithm (GA) (Pal, 2013; Ullah et al., 2012) and modern algorithms such as Random Forest (RF) and Support Vector Machine (SVM) (Archibald and Fann, 2007; Pal and Foody, 2010; Abdel-Rahman et al., 2013). GA feature selection algorithm has been widely used for remote sensing application due to the simplicity and effective computation time (Yu and Liu, 2003). RF and SVM, on the other hand, are mostly used, since they are efficient when working with large size of data, hence describing its suitability to work with hyperspectral data application (Pal, 2006; Zhang and Ma, 2009; Genuer et al., 2010).

Application of hyperspectral data for urban mapping in the early stage has involved the use of airborne hyperspectral data, which is able to cover large areas and provide adequate spectral information. Previous studies have explored the use of airborne hyperspectral

© COPYRIGHT UPM

data to map roof material, particularly asbestos-cement roofing material (Cilia et al., 2016; Frassy et al., 2014). Although the findings from the studies visualize the ability of utilizing high spectral resolution of hyperspectral data for roof detection, the cost of obtaining airborne hyperspectral data is expensive. Satellite-based hyperspectral data could be used as an alternative data; however, the coarse spatial resolution of the data – for instance, Hyperion data by 30-meter spatial resolution – makes it difficult to produce parcel-level urban materials map (Chakravortty et al., 2015). Hence, exploitation of the spatial and spectral advantages of hyperspectral data and VHR satellite data could be investigated to contribute knowledge towards improving the within-class mapping of roof surfaces in the heterogonous urban environment.

Previously, field spectroscopy was used to investigate the spectral characteristics of urban materials through the development of urban impervious surfaces spectral library (Nasarudin and Shafri, 2011; Ferbern, 2013, Khottaus et al., 2014). However, knowledge of spectral properties useful for urban mapping is still lacking (Deshpane et al., 2013). Hence, the combination of information from field spectroscopy and high spatial resolution of VHR multispectral satellite imagery was explored in this study. The significant wavelengths obtained for roofing class discrimination were utilized by developing them into a new spectral index for mapping application on WorldView-3 satellite imagery. In this way, the technique used in this study could overcome the issue of selecting suitable classification algorithms and image processing methods due to limitations of spectral and spatial resolution of remote sensing data (Lu et al., 2010). This technique was explored to provide an efficient technique of mapping the roof degradation status and contributes to new insight of urban study through spectral index application. This study focuses on concrete and metal roofing materials since concrete roofs are commonly used in Malaysia (Taherzadeh et al., 2014), whereas metal roofs are mostly used for commercial and residential areas (Kriner et al., 2010).

1.2 Problem Statements

Mapping impervious surfaces in urban environments is a challenging task due to the heterogeneity of features, high variation of materials used, and different conditions due to aging and weathering factors. First, the separating impervious surfaces with pervious surfaces is challenging since the urban environment has intense heterogeneity of land covers (Hamedianfar and Shafri, 2015). Besides, the problem of high within-class variations makes it difficult to identify intra-class of impervious surfaces as different materials and surfaces could poses similar spectral information. Hence, using normal pixel-based classification upon multispectral satellite imagery is difficult, as the result will be influenced by inadequate spectral information and textural information (Myint et al., 2011). The pixel-based classification results also often depend on the spatial resolution of remote sensing imagery used. Thus, the technique required proper training site and knowledge on the study area to produce good results of classification.

Secondly, due to the heterogeneity of features that exist in urban environment, mixture of different land cover could present in a single pixel of the image (Du et al., 2014). The mix of land cover in a single pixel will consequently result in the salt-and-pepper effect and misclassification during classification. Therefore, sub-pixel classification analysis was

© COPYRIGHT UPM

introduced to resolve the issue of finding endmembers that could represent urban surfaces class based on homogeneity of pixels over the image (Zhang et al., 2014). Still, the technique is not suitable to be used for urban area, due to the difficulty of identifying pure endmembers for within-class materials classification. Thus, classification will likely be influenced by the presence of unidentified classes resulting in degradation of classification accuracy (Myint et al., 2013). Furthermore, restriction of endmember identified could not be greater than number of spectral bands has limit the material mapping (Deng and Wu, 2013).

Therefore, in order to produce a high accurate classification result, VHR multispectral satellite imagery is often used to provide parcel-level classification for urban mapping. In recent years, object-based classification was utilized to improve the classification of impervious surfaces mapping using VHR multispectral satellite images (Hamedianfar and Shafri, 2014; Lu et al., 2011; Taherzadeh and Shafri, 2013). The advantage of applying segmentation-based classification is one of the ways that could reduce the salt-and-pepper effect, and at the same time, overcome high spectral variations issue in the scene. Despite the advantages offered, the technique has shortcomings: it is time consuming and requires effort to develop proper rule-set for delineation between land covers and within-class features (Lu et al., 2011; Myint et al., 2011). Since pixel-based, sub-pixel based and object-based techniques are highly dependant upon training samples, the techniques are computationally intensive, which makes it less efficient for fast and efficient mapping of roofing types, especially for large geographic area.

Lastly, the suitability of data used is also important to improve roof surface detection. Multispectral VHR satellite data has broad and limited number of bands that are commonly equipped with visible-NIR bands. Subsequently, the spectral band restriction will limit the spectral characterization of heterogeneous features in urban environments (Heldens et al., 2011; Mohammadi, 2011; Van der Linden, Waske, et al., 2007). Therefore, new methods are required to solve the challenges initiated by VHR data. Spectral index techniques have the advantage of producing easy implementation and parameter-free classification schemes. However, limitations in terms of spatial and spectral information of the data used need to be considered to improve the classification result. Previously, field spectroscopy data was used as a basis to characterize impervious surfaces materials and conditions for spectral index implementation on multispectral or airborne hyperspectral, since it offers sufficient spectral information (Shahi et al., 2015; Cilia et al., 2016). Hence, spectral analysis from field spectroscopy data could be considered to support limited spectral information of VHR multispectral satellite data with the aim of improving classification output.

1.3 Significance of Study

Roof mapping is very important for urban monitoring, analysis, and planning. However, the current classification scheme applied for roofing detection through pixel-based, sub pixel-based or object-based methods involving complex processing and not efficient for fast computation of a large area. Hence, this study exploits the usage of field spectroscopy data and WorldView-3 satellite data to overcome the difficulties in discriminating between impervious surfaces through the development of spectral indices, namely

© COPYRIGHT UPM

Normalized Difference Concrete Condition Index (NDCCI) and Normalized Difference Metal Condition Index (NDMCI). Since information on spectral properties for urban material spectra using ground-based spectroradiometers is still limited, the information on spectral characterization of roofing materials could contribute to new knowledge in roof materials mapping (Khottaus et al., 2014). The development of the spectral indices for roof degradation status mapping is significant to efficiently classify the roofing materials and condition. Producing parcel-level roof degradation status map using conventional pixel-based and object-based required an intensive effort. Therefore, the establishment of the spectral indices of NDCCI and NDMCI helps to reduce the complexity of existing classification schemes through exploitation of field spectroscopy and VHR satellite image. Therefore, the findings from this study could also be used as the basis for large-scale assessment using airborne, satellite imagery or unmanned aerial vehicle (UAV) by applying the new indices developed for comprehensive mapping of roofing types instead of using census data and manual inspection. Furthermore, the information of roof materials and conditions is also essential for assessment of urban heat and energy consumption in the city especially for rapid urbanization in South East Asian countries, such as Malaysia, Singapore, and Indonesia (Al-Obaidi et al., 2014).

1.4 Research Objectives

The main aim of this research is to evaluate the ability of field spectroscopy and WorldView-3 data to effectively discriminate between different types of roof materials (inter-class) and roof conditions (intra-class). The specific objectives to be achieved in this study are as follows:

i. To determine the significant spectral wavelengths and significant spectral regions for discrimination of roofing materials and conditions using field spectroscopy data.
ii. To compare the performance of Support Vector Machine (SVM), Random Forest (RF) and Genetic Algorithm (GA) feature selection algorithms in discriminating and classifying roof materials and conditions.
iii. To develop and apply spectra indices for roofing conditions detection of roofing material condition from very high resolution (VHR) satellite data.

1.5 Scope of the Study

This study aimed to characterize and discriminate within-class roofing spectral for mapping purposes. Being aware of the rapid development of built-up areas in the city, this research focuses on the different materials of rooftops used in Malaysia, which include asbestos, concrete, clay and metal roofing types. This study, too, includes the different status of rooftop conditions, which is categorized as new and weathered conditions to provide detailed mapping of roof surfaces. Weathered condition roof surfaces are often covered with lichen and has faded paint. As for metal roofing material, weathered metal roof could be described by rusty condition on the roof surfaces. As for new roofing material, the physical surface of the roof are represent by new and bright paint coat.

© COPYRIGHT UPM

Field spectroscopy data was used in this study to discriminate the roofing materials and conditions through significant wavelengths selection using SVM, RF and GA feature selection algorithms. The algorithms were also used as a way to reduce the dimensional size of the hyperspectral data. Spectral index derived from field spectroscopy data was used as alternative for efficient roofing conditions detection, which could be applied on low-cost VHR satellite imagery such as WorldView-3 data. The constraint of the study was the limited roofing materials available in the study area, which the roofing materials are dominated by concrete and metal roofs only. Therefore, this study excludes the spectral index development for clay and asbestos roof, as the materials are hard to be found in the study area.

1.6 Research Gap

Urban environments are commonly composed of various types of features made from different materials respectively. Therefore, spectral confusion between different impervious surfaces often happen due to heterogeneity of features in urban area (Moreira and Galvão, 2010; Weng, 2012). Apart from that, the physical conditions and surface roughness of impervious surfaces through aging and weathering process also contribute to high variation of within-class (Herold et al., 2006; Shaban and Dikshit, 2001). Hyperspectral remote sensing data was proposed as suitable tool for material delineation since it could provide detail spectral information. Nevertheless, the development of optimal methods for analysing hyperspectral data, however, is still limited since there is no standard approach suggested yet for material classification (Chisense, 2012).

Since less research has been done in investigating the spectral diversity and spectral requirements for the impervious surfaces using remote sensing technology (Weng, 2012), optimum application using hyperspectral data for urban application has become difficult. Furthermore, the issue of difficulties in mapping variations of the impervious surfaces in large-scale assessment still exist due to the lack of a standard approach for that kind of purpose. Therefore, Deshpande et al. (2013) in their study have proposed the need of developing the indices on urban materials to provide new insight in urban mapping. Limitation of spectral and spatial information of remote sensing data also has been mentioned by Weng (2007), suggesting the development of algorithms that could combine spectral and spatial information for effective impervious surfaces extraction in urban areas. Spectral index techniques have been suggested as method for mapping roofing conditions with the use of airborne hyperspectral data to overcome uncertainties of conventional method (Cilia, 2015). However, no spectral indices on roofing materials and conditions have been developed for multispectral VHR satellite data yet. Therefore, this study was conducted to design an effective technique of extracting significant spectral wavelengths that have higher possibility of discriminating and enhancing classification of roof materials and condition. It could also contribute new insights of impervious surfaces study in the remote sensing field through development of relevant spectral indices.

© COPYRIGHT UPM

1.7 Thesis Organization

This thesis was organized into five chapters. Chapter 1 introduces this thesis through an explanation of the following: the background of the research, problem statements, research justification, and the objectives of doing this research.

In chapter 2, the literature review explains topics related to this research in detail. This includes the fundamental of remote sensing technology, background of urban spectral characterization, justification and explanation on operation of the feature selection algorithms and related indices developed for impervious surfaces.

Chapter 3 presents the research methodology, which includes the pre- processing, processing and accuracy assessment. The relevant information and the explanation of data collection, algorithms involves, parameter setting and software used for the processing are stated in this chapter.

Chapter 4 presents the results obtained in this study. The first stage in this chapter consists of results of spectral reflectance of the materials and the location of the significant wavelengths in discriminating between the different types of roofing materials and conditions. The second stage focuses on the results of spectral indices development and the indices assessment. A detailed discussion of the results obtained is provided in this chapter.

Chapter 5 is the conclusion of this research. It discusses the overall conclusion based on the objectives and the results achieved. The recommendations for further research are also included.

© COPYRIGHT UPM

REFERENCES

Abdel-Rahman, E. M., Ahmed, F. B., and Ismail, R. (2013). Random forest regression and spectral band selection for estimating sugarcane leaf nitrogen concentration using EO-1 Hyperion hyperspectral data. *International Journal of Remote Sensing, 34*(2), 712-728.

Abdel-Rahman, E. M., Makori, D. M., Landmann, T., Piiroinen, R., Gasim, S., Pellikka, P., and Raina, S. K. (2015). The Utility of AISA Eagle Hyperspectral Data and Random Forest Classifier for Flower Mapping. *Remote Sensing, 7*(10), 13298-13318.

Adam, E., Mutanga, O., and Rugege, D. (2010). Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: a review. *Wetlands Ecology and Management, 18*(3), 281-296.

Adjorlolo, C., Mutanga, O., Cho, M. A., and Ismail, R. (2013). Spectral resampling based on user-defined inter-band correlation filter: C 3 and C 4 grass species classification. *International Journal of Applied Earth Observation and Geoinformation, 21*, 535-544.

Allen, L., Elias, S., & Lim, C. (2008). *The thermal performance of evaluation of roofing systems and materials in Malaysian Residential Development*. Proceedings of SENVAR, ISESEE, Humanity and Technology. UiTM Shah Alam, Dec 1-3, 2008. UTM Press. pp: 387-395.

Al-Obaidi, K. M., Ismail, M., & Rahman, A. M. A. (2014). Passive cooling techniques through reflective and radiative roofs in tropical houses in Southeast Asia: A literature review. *Frontiers of Architectural Research, 3*(3), 283-297.

Arafat, S. M., Aboelghar, M. A., & Ahmed, E. F. (2013). Crop discrimination using field hyperspectral remotely sensed data. *Advances in Remote Sensing, 2*(2), 63-70.

Archibald, R., and Fann, G. (2007). Feature selection and classification of hyperspectral images with support vector machines. *IEEE Geoscience and Remote Sensing Letters, 4*(4), 674-677.

Arnfield, A. J. (2003). Two decades of urban climate research: a review of turbulence, exchanges of energy and water, and the urban heat island. *International Journal of Climatology, 23*(1), 1-26.

Arnold Jr, C. L., and Gibbons, C. J. (1996). Impervious surface coverage: the emergence of a key environmental indicator. *Journal of the American planning Association, 62*(2), 243-258.

Asbestos in Malaysia (2011). *Malaysian Asbestos Removal Guide.* Retrieved 5 November 2015 from http://malaysia.asbestosremovalguide.com/4/awas-asbestos-danger-in-older-malaysian-homes/

© COPYRIGHT UPM

Bajwa, S. G., and Kulkarni, S. S. (2011). *Hyperspectral Data Mining in: PS Thenkabail, JG Lyon, A. Huete, editors, Hyperspectral Remote Sensing of Vegetation and Agricultural Crops.* New York, CRC Press.

Bania, R. K. (2014). Survey on Feature Selection for Data Reduction.*International Journal of Computer Applications*, *94*(18).

Barnes, K. B., Morgan, J., and Roberge, M. (2001). *Impervious surfaces and the quality of natural and built environments*. Baltimore, Department of Geography and Environmental Planning, Towson University.

Barneva, R., Brimkov, V., Hauptman, H., Jorge, R., and Tavares, J. (2010). Computational Modeling of Objects Represented in Images, 2nd International Symposium, CompIMAGE. LNCS, vol. 6026: Springer, Berlin.

Barry, P. S., C., and Carman, S. (2001). EO-1 Hyperion science Data User's Guide. *TRW Space, Defense and Information Systems, 1*(7), 1-65.

Bassani, C., Cavalli, R. M., Cavalcante, F., Cuomo, V., Palombo, A., Pascucci, S., and Pignatti, S. (2007). Deterioration status of asbestos-cement roofing sheets assessed by analyzing hyperspectral data. *Remote Sensing of Environment, 109*(3), 361-378.

Bauer, M. E., Heinert, N. J., Doyle, J. K., and Yuan, F. (2004). *Impervious surface mapping and change monitoring using Landsat remote sensing.* Proceedings of the ASPRS annual conference. Denver, Colorado, May 23-28, 2004.

Bazi, Y., and Melgani, F. (2006). Toward an optimal SVM classification system for hyperspectral remote sensing images. *Geoscience and Remote Sensing, IEEE Transactions on, 44*(11), 3374-3385.

Beleites, C., Steiner, G., Sowa, M., Baumgartner, R., Sobottka, S., Schackert, G., and Salzer, R. (2005). Classification of human gliomas by infrared imaging spectroscopy and chemometric image processing. *Vibrational spectroscopy, 38*(1), 143-149.

Ben-Dor, E., Schläpfer, D., Plaza, A. J., and Malthus, T. (2013). Hyperspectral remote sensing. *Airborne Measurements for Environmental Research: Methods and Instruments*, 413-456.

Berdahl, P., Akbari, H., Levinson, R., and Miller, W. A. (2008). Weathering of roofing materials–an overview. *Construction and Building Materials, 22*(4), 423-433.

Blaschke, T., and Strobl, J. (2001). What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. *GeoBIT/GIS, 6*(01), 12-17.

Boardman, J. W. (1995). *Analysis, understanding, and visualization of hyperspectral data as convex sets in n space.* In SPIE's 1995 Symposium on OE/Aerospace Sensing and Dual Use Photonics. FL, United States, April 17, 1995.

© COPYRIGHT UPM

Bouzekri, S., Lasbet, A. A., and Lachehab, A. (2015). A New Spectral Index for Extraction of Built-Up Area Using Landsat-8 Data. *Journal of the Indian Society of Remote Sensing*, *43*(4), 867-873.

Breiman, L. (2001). Random forests. *Machine learning*, *45*(1), 5-32.

Cadenasso, M. L., Pickett, S. T., and Schwarz, K. (2007). Spatial heterogeneity in urban ecosystems: reconceptualizing land cover and a framework for classification. *Frontiers in Ecology and the Environment*, *5*(2), 80-88.

Camps-Valls, G., and Bruzzone, L. (2005). Kernel-based methods for hyperspectral image classification. *IEEE Transactions on Geoscience and Remote Sensing*, *43*(6), 1351-1362.

Camps-Valls, G., Tuia, D., Gómez-Chova, L., Jiménez, S., & Malo, J. (2011). Remote sensing image processing. *Synthesis Lectures on Image, Video, and Multimedia Processing*, *5*(1), 1-192.

Cateni, S., Vannucci, M., Vannocci, M., and Colla, V. (2012). Variable selection and feature extraction through artificial intelligence techniques. *Multivariate Analysis in Management, Engineering and the Science*, 103-118.

Chakravortty, S., Sinha, D., & Bhondekar, A. (2015). *Assessment of urbanization of an area with hyperspectral image data*. Proceedings of the 3rd International Conference on Frontiers of Intelligent Computing: Theory and Applications (FICTA) 2014. India, Springer International Publishing. pp: 315-322.

Chavez, P., Guptill, S., and Bowell, J. (1984). Image processing techniques for thematic mapper data. *Proceedings, ASPRS-ACSM Technical Papers*, *2*, 728-742.

Chen, C. H., Pau, L. F., and Wang, P. S. P. (2010). *Handbook of pattern recognition and computer vision* (Vol. 27). Singapore, World Scientific. ISBN: 9810211368.

Chen, C. M., and Hepner, G. F. (2001). *Investigation of imaging spectroscopy for discriminating urban land covers and surface materials.* PhD Thesis, Department of Geography, University of Utah.

Chen, P. (2002). *The implications of thermal comfort in New Zealand house design.* PhD Thesis, University of Auckland.

Chen, Y., Wen, D., Jing, L., and Shi, P. (2007). Shadow information recovery in urban areas from very high resolution satellite imagery. *International Journal of Remote Sensing*, *28*(15), 3249-3254.

Chisense, C., Hahn, M., and Engels, J. (2012). Classification of roof materials using hyperspectral data. *Proceedings of the International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. Melbourne, Australia, Aug 25- Sept. 1, 2012. pp: 103-107.

© COPYRIGHT UPM

Chithra, S. V., Nair, M. H., Amarnath, A., & Anjana, N. S. (2015). Impacts of impervious surfaces on the environment. *International Journal of Engineering Science. Invention, 4*(5), 27-31.

Christopherson, R. W. (2010). *Elementan Geosystems - 6th edition*. Boston, Pearson.

Cilia, C., Panigada, C., Rossini, M., Candiani, G., Pepe, M., and Colombo, R. (2015). Mapping of Asbestos Cement Roofs and Their Weathering Status Using Hyperspectral Aerial Images. *ISPRS International Journal of Geo-Information, 4*(2), 928-941.

Clark, S. E., Steele, K. A., Spicher, J., Siu, C. Y., Lalor, M. M., Pitt, R., and Kirby, J. T. (2008). Roofing materials' contributions to storm-water runoff pollution. *Journal of Irrigation and Drainage Engineering, 134*(5), 638-645.

Cortes, C., and Vapnik, V. (1995). Support-vector networks. *Machine learning, 20*(3), 273-297.

Delalieux, S., van Aardt, J. A., Zarco-Tejada, P. J., Kempeneers, P., Verstraeten, W. W., and Coppin, P. (2007). Development of robust hyperspectral indices for the detection of deviations of normal plant state. *EARSeL eProceedings, 6*(2), 82-93.

Deng, C., and Wu, C. (2012). BCI: A biophysical composition index for remote sensing of urban environments. *Remote Sensing of Environment, 127*, 247-259.

Deng, C., and Wu, C. (2013). A spatially adaptive spectral mixture analysis for mapping subpixel urban impervious surface distribution. *Remote Sensing of Environment, 133*, 62-70

Deshpande, S., Inamdar, A., and Vin, H. (2013). Overview of Hyperspectral Remote Sensing of Impervious Surfaces in Urban Environment. *Geo-Informatics in Resource Management and Sustainable Ecosystem. 398*, 128-140.

Dieterle, F. J. (2003). *Multianalyte quantifications by means of integration of artificial neural networks, genetic algorithms and chemometrics for time-resolved analytical data.* PhD Thesis, Universität Tübingen.

Dinç, S., and Aygün, R. S. (2013). Evaluation of hyperspectral image classification using random forest and Fukunaga-koontz transform. *Machine Learning and Data Mining in Pattern Recognition*. *7988*, 234-245.

Du, P., Liu, S., Liu, P., Tan, K., & Cheng, L. (2014). Sub-pixel change detection for urban land-cover analysis via multi-temporal remote sensing images. *Geo-spatial Information Science, 17*(1), 26-38.

Eletta, O.A.A , and Oyeyipo, J.O. (2008). Rain Water Harvesting: Effect of Age of Roof on Water Quality. *International Journal of Applied Chemistry, 4*(2), 157-162.

© COPYRIGHT UPM

Ellingsen, P. G., Reitan, N. K., Pedersen, B. D., & Lindgren, M. (2013). Hyperspectral analysis using the correlation between image and reference. *Journal of Biomedical Optics, 18*(2), 020501-020501.

Falcone, J. A., and Gomez, R. (2005). Mapping impervious surface type and sub-pixel abundance using hyperion hyperspectral imagery. *Geocarto International, 20*(4), 3-10.

Frassy, F., Candiani, G., Maianti, P., Marchesi, A., Nodari, F. R., Rusmini, M., Gianinetto, M. (2012). *Airborne remote sensing for mapping asbestos roofs in Aosta Valley*. Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS). July 22-27, 2012. pp: 7541-7544.

Frazer, L. (2005). Paving paradise: the peril of impervious surfaces. *Environmental Health Perspectives, 113*(7), A456.

Freitas, A. A. (2013). *Data mining and knowledge discovery with evolutionary algorithms*. Springer Science & Business Media.

Goetz, A. (1992). Imaging spectrometry for Earth observations. *Episodes, 15*(1), 7-14.

Goetz, A. F. (2009). Three decades of hyperspectral remote sensing of the Earth: A personal view. *Remote Sensing of Environment, 113*, S5-S16.

Golberg, D. E. (1989). Genetic algorithms in search, optimization, and machine learning. *Addion wesley, 1989*.

Green, R. O., Eastwood, M. L., Sarture, C. M., Chrien, T. G., Aronsson, M., Chippendale, B. J., Faust, J.A., Pavri, B.E., Chovit, C.J., Solis, M. and Olah, M.R. (1998). Imaging spectroscopy and the airborne visible/infrared imaging spectrometer (AVIRIS). *Remote Sensing of Environment, 65*(3), 227-248.

Grefenstette, J. J. (1986). Optimization of control parameters for genetic algorithms. *IEEE Transactions on Systems, Man and Cybernetics, 16*(1), 122-128.

Grimm, N. B., Faeth, S. H., Golubiewski, N. E., Redman, C. L., Wu, J., Bai, X., & Briggs, J. M. (2008). Global change and the ecology of cities. *Science, 319*(5864), 756-760.

Grimm, R., Behrens, T., Märker, M., and Elsenbeer, H. (2008). Soil organic carbon concentrations and stocks on Barro Colorado Island-digital soil mapping using Random Forests analysis. *Geoderma, 146*(1), 102-113.

Grimmond, S. (2007). Urbanization and global environmental change: local effects of urban warming. *The Geographical Journal, 173*(1), 83-88.

Guindon, B., Zhang, Y., and Dillabaugh, C. (2004). Landsat urban mapping based on a combined spectral–spatial methodology. *Remote Sensing of Environment, 92*(2), 218-232.

© COPYRIGHT UPM

Guyon, I., and Elisseeff, A. (2003). An introduction to variable and feature selection. *The Journal of Machine Learning Research, 3*, 1157-1182.

Guyon, I., Weston, J., Barnhill, S., and Vapnik, V. (2002). Gene selection for cancer classification using support vector machines. *Machine Learning, 46*(1-3), 389-422.

Hamedianfar, A., and Shafri, H. Z. (2014). Development of fuzzy rule-based parameters for urban object-oriented classification using very high resolution imagery. *Geocarto International, 29*(3), 268-292.

Hamedianfar, A., & Shafri, H. Z. M. (2015). Detailed intra-urban mapping through transferable OBIA rule sets using WorldView-2 very-high-resolution satellite images. *International Journal of Remote Sensing, 36*(13), 3380-3396.

Hamedianfar, A., & Shafri, H. Z. M. (2016). Integrated approach using data mining-based decision tree and object-based image analysis for high-resolution urban mapping of WorldView-2 satellite sensor data. *Journal of Applied Remote Sensing, 10*(2), 025001-025001.

Hansen, R. E. (2011). *Introduction to synthetic aperture sonar*. INTECH Open Access Publisher.

Haq, M. A., Jain, K., and Menon, K. (2012). Development of new thermal ratio index for snow/ice identification. *International Journal of Soft Computing and Engineering 1*(6), 2231-2307.

Hashim, N., and Rainis, R. (2003). *Urban Ecosystem Studies in Malaysia: A Study of Change*. Florida, USA, Universal Publishers. ISBN: 1581125887.

Havelock, D., Kuwano, S., & Vorländer, M. (Eds.). (2008). *Handbook of signal processing in acoustics*. New York, USA, Springer Science & Business Media. ISBN: 9780387776989.

Heiden, U., Roessner, S., Segl, K., and Kaufmann, H. (2001). *Analysis of spectral signatures of urban surfaces for their identification using hyperspectral HyMap data.* Proceedings of the Remote Sensing and Data Fusion over Urban Areas, IEEE/ISPRS Joint Workshop 2001. Rome, Nov. 8-9, 2001. IEEE Xplore Press. pp: 173-177.

Heiden, U., Segl, K., Roessner, S., and Kaufmann, H. (2005). *Determination and verification of robust spectral features for an automated classification of sealed urban surfaces.* Proceedings of the 4th EARSeL Workshop on Imaging Spectroscopy, Warsaw, Poland, April 27-30, 2005. pp: 165-174.

Heiden, U., Segl, K., Roessner, S., and Kaufmann, H. (2007). Determination of robust spectral features for identification of urban surface materials in hyperspectral remote sensing data. *Remote Sensing of Environment, 111*(4), 537-552.

© COPYRIGHT UPM

Heldens, W., Heiden, U., Esch, T., Stein, E., and Müller, A. (2011). Can the future EnMAP mission contribute to urban applications? A literature survey. *Remote Sensing, 3*(9), 1817-1846.

Herold, M., and Roberts, D. (2005). Spectral characteristics of asphalt road aging and deterioration: implications for remote-sensing applications. *Applied Optics, 44*(20), 4327-4334.

Herold, M., Roberts, D. A., Gardner, M. E., and Dennison, P. E. (2004). Spectrometry for urban area remote sensing—Development and analysis of a spectral library from 350 to 2400 nm. *Remote Sensing of Environment, 91*(3), 304-319.

Herold, M., Schiefer, S., Hostert, P., and Roberts, D. A. (2006). Applying imaging spectrometry in urban areas. *Urban Remote Sensing*, 137-161.

Hsu, C. W., Chang, C. C., and Lin, C. J. (2003). A practical guide to support vector classification. Department of Computer Science, National Taiwan University.

Hunt, G. R. (1977). Spectral signatures of particulate minerals in the visible and near infrared. *Geophysics, 42*(3), 501-513.

Hurd, J. D., and Civco, D. L. (2004). *Temporal characterization of impervious surfaces for the State of Connecticut.* Proceedings of the ASPRS Annual Conference Proceedings. Denver, Colorado, May 23-28, 2004.

Jensen, J. R. (2005). *Introductory digital image processing: A remote sensing perspective*. United States, Pearson College Division.

Jović, A., Brkić, K., & Bogunović, N. (2015). *A review of feature selection methods with applications.* Proceedings of the 38th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), 2015. (pp. 1200-1205). May 25-29, 2015. IEEE Xplore Press. pp: 1200-1205.

Karegowda, A. G., Jayaram, M., & Manjunath, A. (2010). Feature subset selection problem using wrapper approach in supervised learning. *International journal of Computer Applications, 1*(7), 13-17.

Kaya, G. T., Kaya, H., and Ersoy, O. K. (2012). *Feature selection by high dimensional model representation and its application to remote sensing.* Proceedings of the Geoscience and Remote Sensing Symposium (IGARSS), 2012 IEEE International. Munich, Germany, July 22-27, 2012. IEEE Xplore Press. pp: 4938-4941.

Kaya, G. T., Torun, Y., and Kucuk, C. (2014). *Recursive feature selection based on non-parallel SVMs and its application to hyperspectral image classification.* Proceedings of the Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International. Quebec, Canada, July 13-18, 2014. IEEE Xplore Press. pp: 3558-3561.

© COPYRIGHT UPM

Knödel, K., Lange, G., and Voigt, H. J. (2007). *Environmental geology: handbook of field methods and case studies*. Gernamy, Springer Science & Business Media. ISBN: 9783540746690.

Kohavi, R., and John, G. H. (1997). Wrappers for feature subset selection. *Artificial intelligence, 97*(1), 273-324.

Koonsanit, K., Jaruskulchai, C., and Eiumnoh, A. (2012). Band selection for dimension reduction in hyper spectral image using integrated information gain and principal components analysis technique. *International Journal of Machine Learning and Computing, 2*(3), 248-251.

Kotthaus, S., Smith, T. E., Wooster, M. J., and Grimmond, C. (2014). Derivation of an urban materials spectral library through emittance and reflectance spectroscopy. *ISPRS Journal of Photogrammetry and Remote Sensing, 94*, 194-212.

Kriner, S., and James, M. (2010). *Cool Metal Roofing: Crowning the Building Envelope with Energy Efficiency and Sustainability*. Proceedings of the Symposium On Building Envelope Technology. San Antonio, Texas.

Kriner, S., James, M., & Haddock, R. (2010). *Metal Roofing: A Platform For Renewable Energy Systems*. Symposium on Building Envelope Technology. Glenview, November 2010.

Kuenzer, C., Ottinger, M., Wegmann, M., Guo, H., Wang, C., Zhang, J., Dech, S. and Wikelski, M. (2014). Earth observation satellite sensors for biodiversity monitoring: potentials and bottlenecks. *International Journal of Remote Sensing, 35*(18), 6599-6647.

Kumar, R., and Silva, L. (1973). Light ray tracing through a leaf cross section. *Applied Optics, 12*(12), 2950-2954.

Kumar, V., & Minz, S. (2014). Feature Selection. *SmartCR, 4*(3), 211-229.

Lacherade, S., Miesch, C., Briottet, X. and Le Men, H. (2005). Spectral variability and bidirectional reflectance behaviour of urban materials at a 20cm spatial resolution in the visible and nearinfraredn wavelengths a case study over Toulouse (France). *International Journal of Remote Sensing, 26*(17), 3859–3866.

Lachérade, S., Miesch, C., Lemaitre, F., Briottet, X., Le Men, H., Boldo, D., and Valorge, C. (2005). *Analysis of the spectral variability of urban materials for classification. A case study over Toulouse (France).* Proceedings of the 3rd International Symposium Remote Sensing and Data Fusion Over Urban Area (URBAN 2005). Arizona State University, March 13, 2005.

Le Bris, A., Chehata, N., Briottet, X., & Paparoditis, N. (2016). *Spectral Band Selection for Urban Material Classification Using Hyperspectral Libraries*. Proceedings of the ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences. Prague, Czech Republic, July 12-19, 2016. pp: 33-40.

© COPYRIGHT UPM

Lemp, D., and Weidner, U. (2005). *Improvements of roof surface classification using hyperspectral and laser scanning data.* Proceedings of the URBAN 2005 Workshop. Arizona State university, March 13, 2005.

Li, D., Bou-Zeid, E., and Oppenheimer, M. (2014). The effectiveness of cool and green roofs as urban heat island mitigation strategies. *Environmental Research Letters, 9*(5), 055002.

Li, S., Wu, H., Wan, D., and Zhu, J. (2011). An effective feature selection method for hyperspectral image classification based on genetic algorithm and support vector machine. *Knowledge-Based Systems, 24*(1), 40-48.

Li, W. (2008). *Understand the social impact of green---evaluation of the impacts of urban vegetation on neighborhood crime*. PhD Thesis, University of California, Berkeley. ProQuest.

Li, Y., Gong, P., and Sasagawa, T. (2005). Integrated shadow removal based on photogrammetry and image analysis. *International Journal of Remote Sensing, 26*(18), 3911-3929.

Licciardi, G. A. (2014). Hyperspectral Data in Urban Areas. Encyclopedia of Earthquake Engineering. pp: 1-12.

Lillesand, T., Kiefer, R., and Chipman, J. (2000). *Remote sensing and image analysis*. New York, John Wiley and Sons.

Lin, K. M., and Lin, C. J. (2003). A study on reduced support vector machines. *IEEE transactions on Neural Networks, 14*(6), 1449-1459.

Ling, F., and Fu, B. (2009). *Super-resolution mapping of urban buildings with remotely sensed imagery based on prior shape information.* Proceedings of the Joint Urban Remote Sensing Event 2009. Shanghai, China, May 20-22, 2009. IEEE Xpolre Press. pp: 1-5.

Liu, C., Shao, Z., Chen, M., and Luo, H. (2013). MNDISI: a multi-source composition index for impervious surface area estimation at the individual city scale. *Remote Sensing Letters, 4*(8), 803-812.

Liu, H., and Motoda, H. (1998). *Feature extraction, construction and selection: A data mining perspective*: Springer Science & Business Media.

Lu, D., Hetrick, S., and Moran, E. (2010). Land cover classification in a complex urban-rural landscape with QuickBird imagery. *Photogrammetric Engineering & Remote Sensing, 76*(10), 1159-1168.

Lu, D., Hetrick, S., & Moran, E. (2011). Impervious surface mapping with Quickbird imagery. *International Journal of Remote Sensing, 32*(9), 2519-2533.

© COPYRIGHT UPM

Lu, D., and Weng, Q. (2004). Spectral mixture analysis of the urban landscape in Indianapolis with Landsat ETM+ imagery. *Photogrammetric Engineering & Remote Sensing, 70*(9), 1053-1062.

Lu, D., and Weng, Q. (2006). Use of impervious surface in urban land-use classification. *Remote Sensing of Environment, 102*(1), 146-160.

Lu, D., and Weng, Q. (2009). Extraction of urban impervious surfaces from an IKONOS image. *International Journal of Remote Sensing, 30*(5), 1297-1311.

Lundquist, P. B. (2015). *U.S. Patent No. 20,150,049,326*. Washington, DC. Patent and Trademark Office.

Lunetta, R. S. (1998). Applications, project formulation, and analytical approach. *Remote sensing change detection: Environmental Monitoring Methods and Applications*, 1-19.

Luther, J. E., and Carroll, A. L. (1999). Development of an index of balsam fir vigor by foliar spectral reflectance. *Remote Sensing of Environment, 69*(3), 241-252.

Ma, B., Dwyer, L. M., Costa, C., Cober, E. R., and Morrison, M. J. (2001). Early prediction of soybean yield from canopy reflectance measurements. *Agronomy Journal, 93*(6), 1227-1234.

Maggioni, M., Davis, G. L., Warner, F. J., Geshwind, F. B., Coppi, A. C., DeVerse, R. A., and Coifman, R. R. (2006). *Algorithms from signal and data processing applied to hyperspectral analysis: Discriminating normal and malignant microarray colon tissue sections using a novel digital mirror device system*.

Martínez-Usó, A., Pla, F., Sotoca, J. M., and García-Sevilla, P. (2007). Clustering-based hyperspectral band selection using information measures. *IEEE Transaction on Geoscience and Remote Sensing, 45*(12), 4158-4171.

McCoy, R. M. (2005). *Field methods in remote sensing*. New York, Guilford Press. ISBN: 1593850794.

McMahon, G. (2007). Consequences of land-cover misclassification in models of impervious surface, *Photogrammetric Engineering & Remote Sensing, 73*(12), 1343–1353.

Miller, J. D., Kim, H., Kjeldsen, T. R., Packman, J., Grebby, S., and Dearden, R. (2014). Assessing the impact of urbanization on storm runoff in a peri-urban catchment using historical change in impervious cover. *Journal of Hydrology, 515*, 59-70.

Milton, E. J. (2004). Field spectroscopy. *Geoinformatics, Encyclopaedia of Life Support Systems (EOLSS).* Oxford, UK: EOLSS Publishers.

Mohammadi, M. (2011). *Road classification and condition determination using hyperspectral imagery*. Master Thesis, University of Applied Sciences Stuttgart, Germany.

© COPYRIGHT UPM

Moran, E. F. (2010). Land cover classification in a complex urban-rural landscape with QuickBird imagery. *Photogrammetric Engineering and Remote Sensing, 76*(10), 1159.

Momeni, R., Aplin, P., & Boyd, D. S. (2016). Mapping Complex Urban Land Cover from Spaceborne Imagery: The Influence of Spatial Resolution, Spectral Band Set and Classification Approach. *Remote Sensing, 8*(2), 88.

Moreira, R., and Galvão, L. (2010). Variation in spectral shape of urban materials. *Remote Sensing Letters, 1*(3), 149-158.

Mori, M., Iwata, T., Minami, Y., Kato, S., and Akamatsu, Y. (2008). *Spectral analysis of building materials used in Japan*. proceedings of the International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Beijing, July 3-11, 2008. pp: 49-54.

Mountrakis, G., Im, J., and Ogole, C. (2011). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing, 66*(3), 247-259.

Mureriwa, N., Adam, E., Sahu, A., & Tesfamichael, S. (2016). Examining the Spectral Separability of Prosopis glandulosa from Co-Existent Species Using Field Spectral Measurement and Guided Regularized Random Forest. *Remote Sensing, 8*(2), 144.

Myint, S. W., Mesev, V., Quattrochi, D., & Wentz, E. A. (2013). *Urban Image Classification: Per-Pixel Classifiers, Sub-Pixel Analysis, Object-Based Image Analysis, and Geospatial Methods. 10; Chapter*. United States, Taylor & Francis.

Myint, S. W., Gober, P., Brazel, A., Grossman-Clarke, S., & Weng, Q. (2011). Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery. *Remote Sensing of Environment, 115*(5), 1145-1161.

Nahr, S. T., Pahlavani, P., and Hasanlou, M. (2014). Different Optimal Band Selection of Hyperspectral Images Using a Continuous Genetic Algorithm. *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences, 40*(2), 249.

Narra, S. (2007). *Evaluation of Sensing and Machine Vision Techniques in Stress Detection and Quality Evaluation of Turfgrass Species*. PhD Thesis, University of Illinois at Urbana-Champaign, ProQuest.

Nasarudin, N. E. M., and Shafri, H. (2011). Development And Utilization Of Urban Spectral Library For Remote Sensing Of Urban Environment (doi: 10.4090/juee. 2011. v5n1. 044056). *Journal of Urban and Environmental Engineering (JUEE), 5*(1).

Nguyen, H. V., and Gopalkrishnan, V. (2010). Feature extraction for outlier detection in high-dimensional spaces. *Journal of Machine Learning Research, 10*, 66-75.

© COPYRIGHT UPM

Nguyen, M. H., and De la Torre, F. (2010). Optimal feature selection for support vector machines. *Pattern recognition, 43*(3), 584-591.

Noronha, V., Herold, M., Roberts, D., and Gardner, M. (2002). *Spectrometry and Hyperspectral Remote Sensing for Road Centerline Extraction and Evaluation of Pavement Condition.* Proceedings of the Pecora Conference. Denver, Colorado, November 10-15, 2002.

Pahlavani, P., Hasanlou, M., & Nahr, S. T. (2016). Band Selection and Dimension Estimation for Hyperspectral Imagery—a New Approach Based on Invasive Weed Optimization. *Journal of the Indian Society of Remote Sensing*, 1-13.

Pal, M. (2013). Hybrid genetic algorithm for feature selection with hyperspectral data. *Remote Sensing Letters, 4*(7), 619-628.

Pal, M., and Foody, G. M. (2010). Feature selection for classification of hyperspectral data by SVM. *Geoscience and Remote Sensing, IEEE Transactions on, 48*(5), 2297-2307.

Peddle, D. R., White, H. P., Soffer, R. J., Miller, J. R., and LeDrew, E. F. (2001). Reflectance processing of remote sensing spectroradiometer data. *Computers & geosciences, 27*(2), 203-213.

Peng, L. L., and Jim, C. (2015). Economic evaluation of green-roof environmental benefits in the context of climate change: The case of Hong Kong. *Urban Forestry & Urban Greening, 14*(3), 554-561.

Prasad, A. M., Iverson, L. R., and Liaw, A. (2006). Newer classification and regression tree techniques: bagging and random forests for ecological prediction. *Ecosystems, 9*(2), 181-199.

Preet, P., and Batra, S. S. (2015). Feature Selection for classification of hyperspectral data by minimizing a tight bound on the VC dimension. *arXiv preprint arXiv:1509.08112*.

Prospere, K., McLaren, K., and Wilson, B. (2014). Plant species discrimination in a tropical wetland using in situ hyperspectral data. *Remote Sensing, 6*(9), 8494-8523.

Ratnadeep Ray, A. K. P., Balen B. (2014). OIF Based Indeces Oriented Ecological Classification Using LANDSAT TM Digital Data – A Case Study on Beluchary and Dhulibasan Island Groups, Sunderban, West Bengal, India. *International Journal of Remote Sensing Applications, 4*(1), 56 - 60.

Reutebuch, S. E., Andersen, H. E., & McGaughey, R. J. (2005). Light detection and ranging (LIDAR): an emerging tool for multiple resource inventory. *Journal of Forestry*, *103*(6), 286-292.

Richards, J. A., and Jia, X. (2006). Interpretation of hyperspectral image data. *Remote Sensing Digital Image Analysis: An Introduction*, 359-388.

© COPYRIGHT UPM

Ridd, M. K. (1995). Exploring a VIS (vegetation-impervious surface-soil) model for urban ecosystem analysis through remote sensing: comparative anatomy for cities†. *International Journal of Remote Sensing, 16*(12), 2165-2185.

Saeys, Y., Inza, I., and Larrañaga, P. (2007). A review of feature selection techniques in bioinformatics. *Bioinformatics, 23*(19), 2507-2517.

Santos, A., Celes, C. d. S., Araújo, A. d. A., and Menotti, D. (2012). *Feature selection for classification of remote sensed hyperspectral images: A filter approach using genetic algorithm and cluster validity.* Proceedings of the 2012 International Conference on Image Processing, Computer Vision, and Pattern Recognition (IPCV'12). Nevada, USA, July 16-19, 2012.

Schaepman-Strub, G., Schaepman, M. E., Martonchik, J., Painter, T., and Dangel, S. (2009). Radiometry and reflectance: from terminology concepts to measured quantities. *The SAGE Handbook of Remote Sensing*, 215.

Schaepman, M. E., Ustin, S. L., Plaza, A. J., Painter, T. H., Verrelst, J., and Liang, S. (2009). Earth system science related imaging spectroscopy—An assessment. *Remote Sensing of Environment, 113*, S123-S137.

Schmidt, K., and Skidmore, A. (2003). Spectral discrimination of vegetation types in a coastal wetland. *Remote Sensing of Environment, 85*(1), 92-108.

Schueler, T. R., Fraley-McNeal, L., and Cappiella, K. (2009). Is impervious cover still important? Review of recent research. *Journal of Hydrologic Engineering, 14*(4), 309-315.

Serpico, S. B., and Bruzzone, L. (2001). A new search algorithm for feature selection in hyperspectral remote sensing images. *IEEE Transaction on Geoscience and Remote Sensing, 39*(7), 1360-1367.

Shaban, M., and Dikshit, O. (2001). Improvement of classification in urban areas by the use of textural features: the case study of Lucknow city, Uttar Pradesh. *International Journal of Remote Sensing, 22*(4), 565-593.

Shafri, H. Z., Anuar, M. I., and Saripan, M. I. (2009). Modified vegetation indices for Ganoderma disease detection in oil palm from field spectroradiometer data. *Journal of Applied Remote Sensing, 3*(1), 033556-033556-033523.

Shahi, K., Shafri, H. Z., Taherzadeh, E., Mansor, S., and Muniandy, R. (2015). A novel spectral index to automatically extract road networks from WorldView-2 satellite imagery. *The Egyptian Journal of Remote Sensing and Space Science, 18*(1), 27-33.

Simonovic, S. P. (2012). *Floods in a Changing Climate: Risk Management (Vol. 4)*. New York, Cambridge University Press. ISBN: 9781107018747.

Shippert, P. (2003). Introduction to hyperspectral image analysis. *Online Journal of Space Communication, 3*.

© COPYRIGHT UPM

Slonecker, E. T., Jennings, D. B., and Garofalo, D. (2001). Remote sensing of impervious surfaces: A review. *Remote Sensing Reviews, 20*(3), 227-255.

Smith, R. B. (2006). Introduction to hyperspectral imaging with TNTmips. MicroImages, Retrieved on 6 September 2016 from http://www.microimages.com/getstart/pdf/ hyprspec.pdf

Stevens, A., van Wesemael, B., Bartholomeus, H., Rosillon, D., Tychon, B., and Ben-Dor, E. (2008). Laboratory, field and airborne spectroscopy for monitoring organic carbon content in agricultural soils. *Geoderma, 144*(1), 395-404.

Strobl, C., Boulesteix, A.-L., Zeileis, A., and Hothorn, T. (2007). Bias in random forest variable importance measures: Illustrations, sources and a solution. *BMC Bioinformatics, 8*(1), 25.

Sullivan, E. J. (2008). Active Sonar. In D. Havelock, S. Kuwano & M. Vorländer (Eds.), *Handbook of Signal Processing in Acoustics*. New York, NY: Springer New York. pp: 1737-1755.

Suzuki, Y., Yuen, S. R., and Ashley, R. (2005). Short, thin asbestos fibers contribute to the development of human malignant mesothelioma: pathological evidence. *International Journal of Hygiene and Environmental Health, 208*(3), 201-210.

Swanson, A. L., and Helmlinger, M. C. (2014). *Spectral image classification of rooftop condition for use in property insurance*. Google Patents.

Szabó, S., Burai, P., Kovács, Z., Szabó, G., Kerényi, A., Fazekas, I., Szabó, G. (2014). Testing algorithms for the identification of asbestos roofing based on hyperspectral data. *Environmental Engineering and Management Journal, 143*(11), 2875-2880.

Taherzadeh, E., and Shafri, H. Z. (2013). Development of a generic model for the detection of roof materials based on an object-based approach using WorldView-2 satellite imagery. *Advances in Remote Sensing, 2013*.

Taherzadeh, E., Shafri, H. Z., & Shahi, K. (2014). Roof Material Detection Based on Object-Based Approach Using WorldView-2 Satellite Imagery.*World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering, 8*(10), 1821-1824.

Takebayashi, H., and Moriyama, M. (2007). Surface heat budget on green roof and high reflection roof for mitigation of urban heat island. *Building and Environment, 42*(8), 2971-2979.

Tang, J., Alelyani, S., & Liu, H. (2014). Feature selection for classification: A review. *Data Classification: Algorithms and Applications*, 37.

Team, R. C. (2014). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3900051070.

© COPYRIGHT UPM

Teillet, P. (1995). The role of surface observations in support of remote sensing. *Canadian Remote Sensing Contributions to Understanding Global Change, E. LeDrew, M. Strome and F. Hegyi (Eds.), Department of Geography Publication Series*(38), 333-351.

Tobiszewski, M., Polkowska, Ż., Konieczka, P., and Namieśnik, J. (2010). Roofing materials as pollution emitters–concentration changes during runoff. *Polish. Journal of Environmental Studies, 19*, 1019-1028.

Ulrich, T. (2013). Expert Tip: Understand Your Field of View When Taking Reference Measurements. Retrieved 1 November 2015 from http://discover.asdi.com/bid/97740/Expert-Tip-Understand-Your-Field-of-View-When-Taking-Reference-Measurements

United Nations, Department of Economic and Social Affairs, Population Division (2015). *World urbanization prospects: The 2014 Revision, Highlights (ST/ESA/SER.A/352)*. ISBN: 9789222515176.

Unold, O., Dobrowolski, M., Maciejewski, H., Skrobanek, P., and Walkowicz, E. (2012). A GA-Based wrapper feature selection for animal breeding data mining. *Hybrid Artificial Intelligent Systems, 7209*, 200-209.

Van de Voorde, T., De Roeck, T., and Canters, F. (2009). A comparison of two spectral mixture modelling approaches for impervious surface mapping in urban areas. *International Journal of Remote Sensing, 30*(18), 4785-4806.

Van der Linden, S., Janz, A., Waske, B., Eiden, M., and Hostert, P. (2007). Classifying segmented hyperspectral data from a heterogeneous urban environment using support vector machines. *Journal of Applied Remote Sensing, 1*(1), 013543-013543-013517.

Van der Linden, S., Waske, B., Eiden, M., Hostert, P., and Janz, A. (2007). Classifying segmented hyperspectral data from a heterogeneous urban environment using support vector machines. *Journal of Applied Remote Sensing, 1*(1), 013543-013543-013517.

Vegetation Analysis: Using Vegetation Indices in ENVI. Retrieved 30 January 2016 from http://www.exelisvis.com/Learn/WhitepapersDetail/TabId/802/ArtMID/2627/ArticleID/13742/Vegetation-Analysis-Using-Vegetation-Indices-in-ENVI.aspx

Voogt, J. A., and Oke, T. R. (2003). Thermal remote sensing of urban climates. *Remote Sensing of Environment, 86*(3), 370-384.

Wang, H., Khoshgoftaar, T. M., and Gao, K. (2010). *A comparative study of filter-based feature ranking techniques.* Proceedings of the Information Reuse and Integration (IRI) 2010. Las Vegas, USA, August 4-6, 2010. IEEE Xplore Press. pp: 43-48.

© COPYRIGHT UPM

Wang, H., Khoshgoftaar, T. M., and Napolitano, A. (2011). *An Empirical Study of Software Metrics Selection Using Support Vector Machine.* Proceedings of the 23rd International Conference on Software Engineering and Knowledge Engineering. Miami, USA, July 7-9, 2011.

Waqar, M. M., Mirza, J. F., Mumtaz, R., and Hussain, E. (2012). Development of New Indices for Extraction of Built-Up Area & Bare Soil from Landsat Data. *Open Access Scientific Reports, 1*(1).

Weber, C. (2001). Remote sensing data used for urban agglomeration delimitation. *Remote Sensing and Urban Analysis*, 155-167.

Weng, Q. (2007). *Remote sensing of impervious surfaces*. Boca raton, Florida, CRC Press. ISBN: 139781420043747.

Weng, Q. (2012). Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends. *Remote Sensing of Environment, 117*, 34-49.

Weng, Q., Hu, X., and Lu, D. (2008). Extracting impervious surfaces from medium spatial resolution multispectral and hyperspectral imagery: a comparison. *International Journal of Remote Sensing, 29*(11), 3209-3232.

Wu, C. (2009). Quantifying high-resolution impervious surfaces using spectral mixture analysis. *International Journal of Remote Sensing, 30*(11), 2915-2932.

Xu, D., Sun, L., Luo, J., and Liu, Z. (2013). Analysis and denoising of hyperspectral remote sensing image in the curvelet domain. *Mathematical Problems in Engineering, vol. 2013, Article ID 751716*, 11 pages.

Xu, H. (2010). Analysis of impervious surface and its impact on urban heat environment using the normalized difference impervious surface Index (NDISI). *Photogrammetric Engineering & Remote Sensing, 76*(5), 557-565.

Yang, H., Zhang, D., Huang, W., Gao, Z., Yang, X., Li, C., and Wang, J. (2012). Application and Evaluation of Wavelet-Based Denoising Method in Hyperspectral Imagery Data. *Computer and Computing Technologies in Agriculture V, 369*, 461-469, Springer.

Ye, J., and Ji, S. (2010). *Discriminant analysis for dimensionality reduction: An overview of recent developments*. Biometrics: Theory, Methods, and Applications. New York, Wiley-IEEE Press.

Yu, B., Ostland, I. M., Gong, P., and Pu, R. (1999). Penalized discriminant analysis of in situ hyperspectral data for conifer species recognition. *IEEE Transaction on Geoscience and Remote Sensing, 37*(5), 2569-2577.

Yu, B., Ostland, M., Gong, P., and Pu, R. (1999b). Penalized discriminant analysis of in situ hyperspectral data for conifer species recognition. *IEEE Transaction on Geoscience and Remote Sensing, 37*(5), 2569-2577.

© COPYRIGHT UPM

Yu, L., and Liu, H. (2003). *Feature selection for high-dimensional data: A fast correlation-based filter solution.* Proceedings of the 20th International Conference on Machine Learning. Washington, August 21-24, 2003.

Yu, X., and Lu, C. (2014). *Urban percent impervious surface and its relationship with land surface temperature in Yantai City, China.* Proceedings of the IOP Conference Series: Earth and Environmental Science. 17(1), 012163.

Yuan, F., and Bauer, M. E. (2007). Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery. *Remote Sensing of Environment, 106*(3), 375-386.

Zha, Y., Gao, J., and Ni, S. (2003). Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing, 24*(3), 583-594.

Zhang, C., Cooper, H., Selch, D., Meng, X., Qiu, F., Myint, S.W., Roberts, C. and Xie, Z., 2014. Mapping urban land cover types using object-based multiple endmember spectral mixture analysis. *Remote Sensing Letters, 5*(6), pp.521-529.

Zhang, H., Lin, H., Zhang, Y., and Weng, Q. (2015). *Remote Sensing of Impervious Surfaces in Tropical and Subtropical Areas* (Vol. 11). Boca Raton, Florida, CRC Press. ISBN: 13978148225486.

Zhang, Q., and Pierce, F. J. (2013). *Agricultural automation: fundamentals and practices*. Boca Raton, Florida, CRC Press. ISBN: 139781439880579.

Zhang, R., Ma, J., Chen, X., and Tong, Q. (2009). *Feature selection for hyperspectral data based on modified recursive support vector machines.* Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, IGARSS 2009. Cape Town, South Africa, July 12-17, 2009. IEEE Xplore Press. pp: 847-850.

Zhou, Y., and Wang, Y. (2008). Extraction of impervious surface areas from high spatial resolution imagery by multiple agent segmentation and classification. *Photogrammetric Engineering & Remote Sensing, 74*(7), 857-868.

Zhu, Z., Ong, Y.-S., and Dash, M. (2007). Wrapper–filter feature selection algorithm using a memetic framework. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 37*(1), 70-76.

Zhuo, L., Zheng, J., Li, X., Wang, F., Ai, B., and Qian, J. (2008). *A genetic algorithm based wrapper feature selection method for classification of hyperspectral images using support vector machine.* Proceedings of the Geoinformatics 2008 and Joint Conference on GIS and Built Environment: Classification of Remote Sensing Images. Guangzhou, China, June 28, 2008.

© COPYRIGHT UPM