Rule Based Classification for Urban Heat Island Mapping

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SUMMARY

One of the main parameter for urban heat island mapping is the land cover information. Satellite data were used to map the land cover over the study area, CyberJaya. Remotely sensed data were processed using pixel based and object based image processing techniques. Most traditional classification approaches are based exclusively on the digital number of the pixel itself. Thereby only the spectral information is used for the classification. As a result, the use of spectral based classification methods has been repeatedly reported to create confusion among the classes especially on the cloud cover occurred at hilly area always brings the familiar Digital Number (DN) with urban and bare land in the optical remote sensing images. An object-oriented classification is preferred in order to overcome the limitations mentioned above. The technique allows the polygon based classification process. It is based on fuzzy logic, allows the integration of a broad spectrum of different object features, such as spectral values, shape and texture. Sophisticated classification, incorporating contextual and semantic information, can be performed by utilizing not only image objects attributes but also the relationship between networked image objects. The land use classification result was then used to estimate the emissivity values of several features. Land surface temperature of the study area was then computed. Finally, the land surface temperature and the classified land cover theme were then exported to GIS environment for urban heat mapping analysis.

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1. INTRODUCTION

The traditional pixel-based classification normally can be performed by unsupervised and supervised classification. Unsupervised classification has few disadvantages where analyst has little control over image classes - making inter-comparison of data difficult. Besides, spectral properties keep on changing over time, therefore the relationship between spectral response and information class are not constant and detailed spectral knowledge of surfaces may be necessary (Campbell, 1996). An experiment has been carried out to compare the unsupervised and supervised classification. The results showed that the supervised classification achieve higher accuracy than unsupervised classification if the analysts have long known well about the study area. In addition also, supervised classification allows the users to pick out the different regions and different between features that look similar, like clouds and snow. In the unsupervised classification, similar regions were often lumped together (McCready and Hautaniemi, 2000).

In a supervised classification, the identity and location of some of the land cover types, such as urban, agriculture or wetland are known a priori (before the fact) through a combination of fieldwork, analysis or aerial photography, maps and personal experience (Mausel et al., 1990). The analyst attempts to locate specific sites in the remotely sensed data that represent homogeneous examples of these known land cover types. Various supervised classification algorithms may be used to assign an unknown pixel to one of a number of classes. Among the most frequently used classification algorithms are the parallelepiped, minimum distance and maximum likelihood decision rules. Among these algorithms, the maximum likelihood method is generally preferred (Campbell, 1998; Avery and Berlin, 1992). It becomes most commonly used classifier due to its higher accuracy levels. Initially it was not used as much purely due to the large amount of time the images took to process. Now with faster computers, it is used much more frequently. It is generally accepted that this is the most accurate form of classification if compare to parallelepiped and minimum distance algorithms (Curran, 1985).

Anyway, traditional supervised classification has its disadvantages too. The most common error occurred when assigning the classes on training data, in the shape of polygon, pixels are assigned to a specific class if they fall within the polygon regions are allocated to the appropriate categories. Problems occur when pixels fall outside the specific regions or within overlapping regions. This will result in misclassification of data. In the other words, it is very reliant on the accuracy of the training data. Therefore, with box classification the possibilities of having misclassification or unclassified data were high (Kardono, 1992).

In contrast to classic image processing methods, the basic processing units of object-oriented image analysis are image objects or segments and not single pixels; moreover, classification acts on image objects. One motivation for the object-oriented approach is the fact that, in many cases, the expected result of most image analysis tasks is the extraction of real world objects, proper in shape and proper in classification. This expectation cannot be fulfilled by traditional, pixel-based approaches (Baatz and Shape, 1999).

The concept is that important semantic information necessary to interpret an image is not represented in single pixels, but in meaningful image objects and their mutual relations. Image analysis is based on contiguous, homogeneous image regions that are generated by initial image segmentation. Connecting all the regions, the image content is represented as a network of image objects. These image objects act as the building blocks for the subsequent image analysis. In comparison to pixels, image objects carry much more useful information. Thus, they can be characterized by far more properties such as form, texture, neighborhood or context, than pure spectral or spectral derivative information (Baatz and Shape, 2000). This additional information must be describable in an appropriate technique to derive improved classification results.

In relation to urban heat analysis, one of the most significant parameter is the information of the land cover of the area of interest. Land use and land cover changes have environmental implication at local and regional levels, and perhaps are linked to the global environmental process. Because of interrelated nature of the elements of the natural environment, the direct effects on one element may cause indirect effects on others. Urbanization is the conversion of other types of land use associated with growth of population and economy is a main type of land use and land cover change in human history. It has a great impact on climate. By covering with building, roads and other impervious surfaces, urban areas generally have higher solar radiation absorption and a greater thermal capacity and conductivity so that heat is stored during the day and released by night. Therefore, urban areas tend to experience a relatively higher temperature compared with surrounding rural areas. This thermal difference in conjunction with waste heat released from urban houses. Transportation and industry, contribute to the development of urban heat island (Wang, 2001). Urban development usually gives to a dramatic change of the earth's surface as natural vegetation is removed and replaced by non-evaporating and non-transpiring surfaces such as metal, asphalt and concrete. This alteration will inevitably result in the redistribution of incoming solar radiation and induce the urban rural contrast in surface radiance and air temperature.

2. MATERIALS AND METHODS

2.1. Study Area

Cyberjaya is located directly to the west of Putrajaya, which is situated in the District of Sepang at longitude between 101°37' East to 101° 45' East and the Latitude 2° 37' North to 2° 59' North. The landuse in Cyberjaya is about 7074 hectare (17 400 acres) which is land use changing was occur from vegetation area (forest and agriculture), water body, mining area, wetland and small residential are to development area.

In this study, a sub scene of LANDSAT 7 ETM+ image acquired on the 31th May 2001 was used. This sub-scene covers the areas of Cyberjaya and its surrounding areas, including part of the Putrrajaya. This area selected as a study area because the existence of diverse landuse including residential, development area, forest, vegetation, water bodies and others. Figure 1 shows the LANDSAT 7 ETM+ of study area.

Figure 1: LANDSAT 7 ETM+ image of study area

2.2 Object Oriented Classification

Analysis of an image in the object-oriented approach involved classifying the image objects according to class descriptions organized in an appropriate knowledge base. This technique was created by means of inheritance mechanisms, concepts and methods of fuzzy logic and semantic modelling. The process of the object oriented classification mainly involved two sections, which are segmentation and classification.

2.2.1 Multiresolution Segmentation

Segmentation is not an aim in itself. As regards the object-oriented approach to image analysis, the image objects resulting from a segmentation procedure are intended to be rather image object primitives, serving as information carriers and building blocks for further classification or other segmentation processes. In this sense, the best segmentation result is the one that provides optimal information for further processing (Hofmann, Puzicha and Buhmann, 1998).

The eCognition software performs a first automatic processing - segmentation - of the imagery. This results to a condensing of information and a knowledge-free extraction of image objects. The formation of the objects is carried out in a way that an overall homogeneous resolution is kept. The segmentation algorithm does not only rely on the single pixel value, but also on pixel spatial continuity (texture, topology). The organized images objects carry not only the value and statistical information of the pixels of which they consists, but also information on texture and shape as well as their position within the hierarchical network (Humano, 2000; Manakos, 2001).

Figure 2 below shows the concept of segmentation, in which where mainly three different levels of image objects have been created representing different scales. All of the image objects were automatically linked to a network after the segmentation process. Each image object knows its neighbors, thus affording important context information for later analysis. Subsequently, repetition of segmentation with different scale parameter creates a hierarchical network of image objects. Each image object knows its super-object and its sub-objects. The basic difference, especially when compared to pixel-based procedures, is that object oriented analysis does not classify single pixels, but rather image objects which are extracted in a previous image segmentation step.

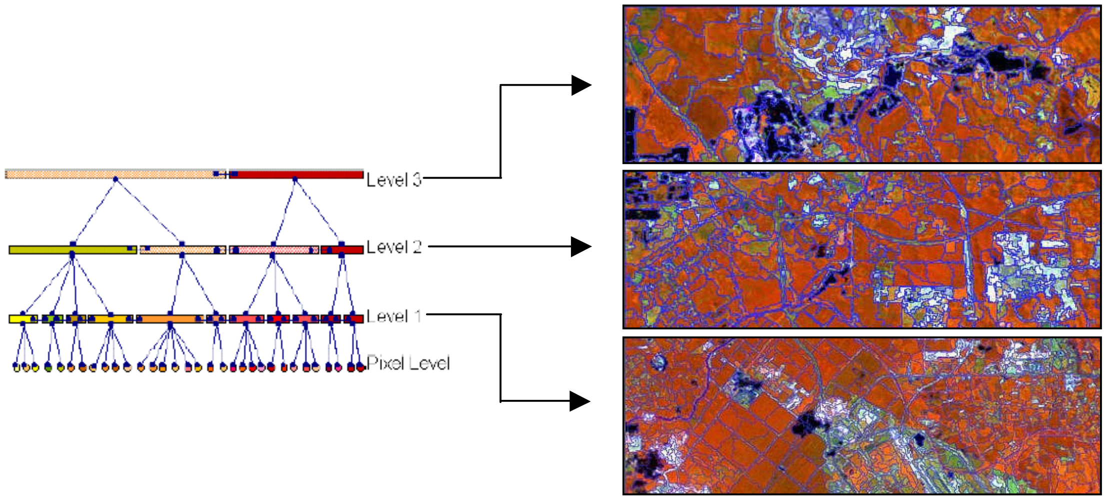


Figure 2: Hierarchical net of image objects derived from image segmentation level 1 (10 pixels scale parameter), level 2 (20 pixels scale parameter) and level 3 (30 pixels scale parameter).

2.2.2 Classification

eCognition supports different supervised classification techniques and different methods to train and build up a knowledge base for the classification of image objects. The frame of knowledge base for the analysis and classification of image objects is the so-called class hierarchy. It contains all classes of a classification scheme. The classes can be grouped in a hierarchical manner allowing the passing down of class descriptions to child classes on the one hand, and meaningful semantic grouping of classes on the other. This simple hierarchical grouping offers an astonishing range for the formulation of image semantics and for different analysis strategies. The user interacts with the procedure and based on statistics, texture, form and mutual relations among objects defines training areas. The classification of an object can then follow the "hard" nearest neighbourhood method or the "soft" method using fuzzy membership functions (Manakos, 2001).

Under the soft method, each class of a classification scheme contains a class description. Each class description consists of a set of fuzzy expressions allowing the evaluation of specific features and their logical operation. A fuzzy rule can have one single condition or can consist of a combination of several conditions that have to be fulfilled for an object to be assigned to a class. The fuzzy sets were defined by membership functions that identify those values of a feature that are regarded as typical, less typical, or not typical of a class, i.e., they have a high, low, or zero membership respectively, of the fuzzy set (Mitri and Gitas, 2002). In this paper, the vegetation and urbanization area is classified by using the external input of Normalized Difference Vegetation Indexes (NDVI).

$$NDVI_{TM} = \frac{(TM4 - TM3)}{(TM4 + TM3)} \text{-------------------Eq. (1)}$$

2.3 Estimation of Surface Temperature

The low gain thermal band (band 6:1) of ETM+ was converted to Ts in four steps, as follows:

– Digital Number (DN) to Spectral Radiance (Ll)

Conversion of the image DN values to spectral radiance is carried out using the gain and offset values given in the image header file (Eq. (2)). Thus

L_l = ((LMAX-LMIN)/(QCALMAX-QCALMIN)) * (QCAL-QCALMIN) + LMIN -------------(2)

Where:

QCALMIN = 1, QCALMAX = 255, and QCAL = Digital Number

LMIN and LMAX = spectral radiance for band 6:1 at DN 0 and 255. These parameters can be found in USGS (2000).

– Spectral Radiance to Black Body Temperature

The ETM+ thermal band data can be converted from spectral radiance Black Body Temperature (BBT) which assumes surface emissivity=1 (Eq. (3))

T = K2 / ln(K1/ Ll+ 1) -------------------(3)

Where:

T = Effective at-satellite temperature in Kelvin

K1 = Calibration constant 1 (W.m2.sr-1)(666.09)

K2 = Calibration constant 2 in K (1282.7)

Ll = Spectral radiance in (W.m2.sr-1)

– Emissivity Correction

The visible wavelength bands of ETM+ image were classified into three main land use/cover classes: vegetation, non-vegetation and water using a supervised classification. Corrections for emissivity differences were carried out by land cover type by ratioing the BBT image with the classified image in which the pixel values for the land cover class were replaced with the corresponding emissivity value. Thus the emissivity corrected surface temperature (Ts) is derived by Equation (4). (Artis and Carnahan 1982).

Ts = T / [1 + (lT / a) ln e] ---------------------(4)

l = Wavelength of emitted radiance,

a = hc/K (1.438 ´ 10-2 mK),

h = Planck's constant (6.26 ´ 10-34 J.sec),

c = velocity of light (2.998 ´ 108 m/sec),

K = Stefan Bolzmann's Constant (1.38 ´ 10-23 J/K).

3 RESULTS AND DISCUSSION

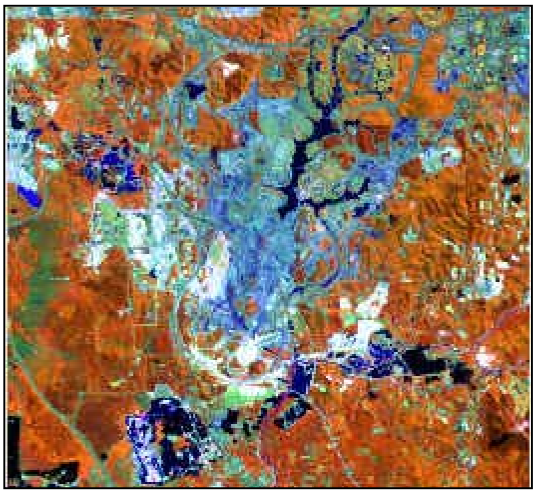


Figure 3

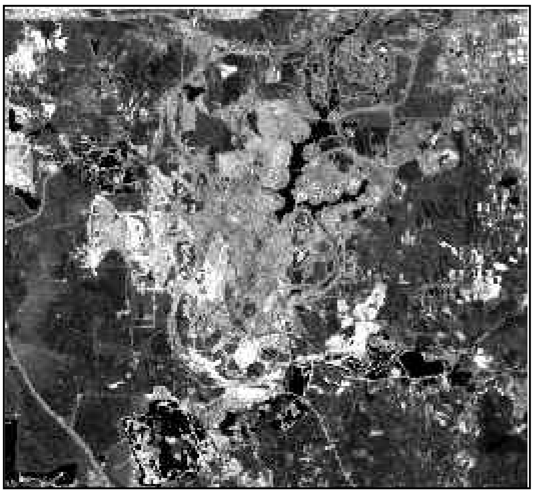


Figure 4

Figure 3: Band combination of channel 4, 5, 3 (RGB) give maximum information in the land use/cover classification.

Figure 4: Thermal band of LANDSAT 7 ETM+

Band combination of channel 4, 5 and 3 are chosen for further classification analysis. Figure 3 shows the image for channel 4, 5 and 3. This combination will give maximum information in the land use/cover classification. The thermal energy responses of different landforms in study area indicates that the variation in surface temperature of different surface patterns. Land surface temperature was extracted from thermal band of Landsat 7 ETM+ and is shown in Figure 4. Analysis from imagery indicates that the commercial/ urban and residential areas are places with highest surface temperature relative to vegetation and water, which exhibit lower temperature.

The object oriented classification result is shown in Figure 5. The structure of class hierarchy is shown in Figure 6 where the improved classification result achieved at level 2. In this study, the distribution of the urban surface temperature is different depending on various land cover types. Figure 7 shows the surface temperature among the different land use types. The urban and development area have shown the higher of surface temperature rather than forest, agriculture/vegetation area and water. A lot of building is one of the factors that more heat reflection occurs and it will raise the surface temperature at urban area rather than the development area. The roof and asphalt makes the reflectivity occur and it causes surface temperature and the overall ambient air temperature in an urban area to rise. Surface temperature for forest and agriculture is between 20ºC to 30°C, this because of vegetation area are normally will absorb until 50% to 70% of heat and some of heat will be reflected at the surface area. The temperature for vegetation area is lower than urban area. The green areas are cooler because dissipate solar energy by absorbing surrounding heat and through an evaporation process from the leaves, thereby cooling the air.

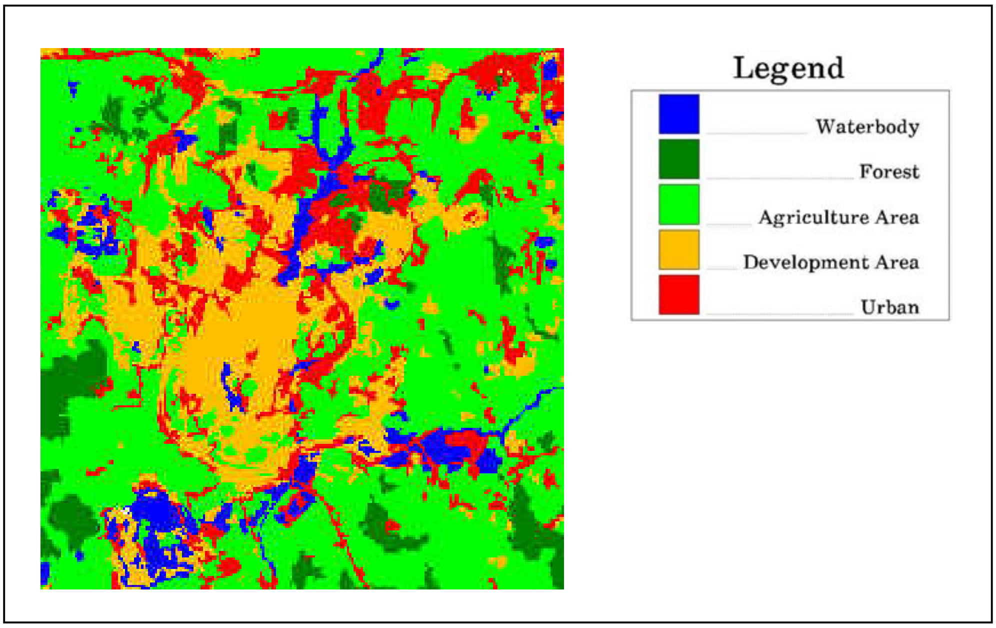


Figure 5: Land cover of the study area

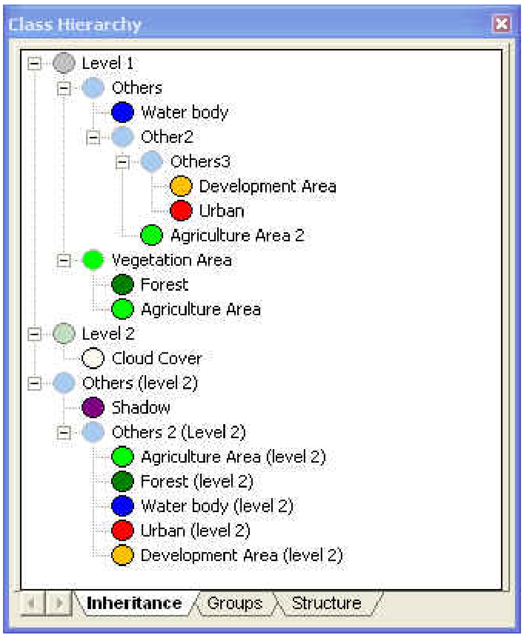
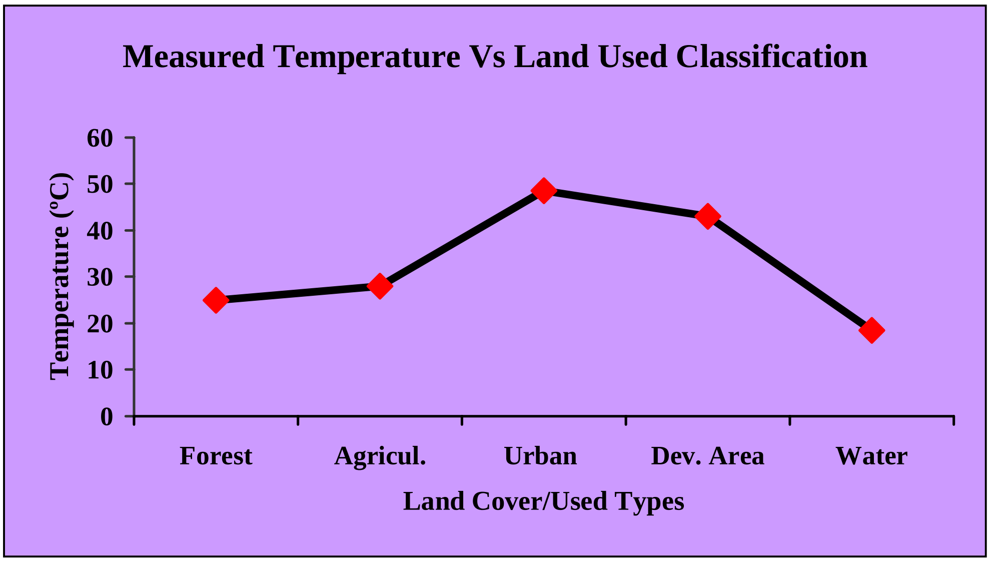


Figure 6: Class hierarchy



Surface Figure 7: Temperature Variation among Different Land use Types

4. CONCLUSIONS

As shown in this study, temperature and land use information can be directly derived from remotely sensed data, which provides a powerful way to monitor urban environment and human activities. This information enhances our understanding of urban environment and can be further used to improve environmental quality.

It is proved that the result of object-oriented analysis is satisfied for land use classification. The possibility of performing classification-based segmentation obviously improved the classification result obtained at the second level. Furthermore, the use of membership functions resulted in a reduction in the number of misclassified pixels.

Discriminating among the different confusion classes was possible using the contextual and spectral information supplied by the images. All steps involved in the image analysis could be recorded as a complete procedure. Thus, the whole strategy for solving a particular problem can be applied to other data of the same type especially applying onto time series data. Besides, it constitutes an important step towards the integration of remote sensing and GIS, by providing operational means of interpretation high-resolution data. This technique is recommended to test on VHR data such as Ikonos image or Aerial photos especially in town area where more details classes can be generated.

REFERENCES

Avery, T.E. and Berlin, G.L. (1992). Fundamentals of Remote Sensing and Airphoto Interpretation.. *Prentice Hall*, Upper Saddle River, New Jersey. Chapter 6.

Baatz, M.A.S. (1999). Object-Oriented and Multi-Scale Image Analysis in Semantic Networks. *In: Proc. Of the 2nd International Symposium on Operationalization of Remote Sensing(Enschede. ITC).*

Baatz, M.A.S. (2000). Multiresolution segmentation - an optimization approach for high quality multi-scale image segmentation. *Angewandte Geographische Informationsverarbeitung XI*.
Campbell, J. (1998). Map Use and Analysis. *WCB/McGraw Hill.* 3rd Ed., Chapter 18, pp 286-295.
Campbell, J.B. (1996). Introduction to Remote Sensing. *New York: Guilford Publications*. 622 p.
Curran, P.J. (1985). Principles of Remote Sensing. Longman *Scientific and Technical Group,* Essex, England. 282pp.
Hofmann, T. PUZICHA, J, and Buhmann, J. (1998). Unsupervised texture segmentation in a deterministic annealing framework. *In: IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 13: 478-482.
Humano, A. (2000). eCogntition and Change Detection-Integrating Aerial Photos and Satellite Images. *http://www.definins.com*. *eCognition Application Notes,* Vol. 1, No. 2, September 2000.
Kardono, P. (1992) The Use of Remote Sensing Techniques in the Detection of Upland Vegetation Communities in the North York Moors National Park. *http:// www.northyorkmoors-npa.gov.uk/Mlandresreviewpdf/8.4.pdf. Unpublished PhD Thesis*, University of St. Andrews.
Manakos, I. (2001). eCognition and Precision Farming. *http://www.lrz-muenchen.de/~lnn/*. *eCognition Application Notes*, Vol. 2, No 2, April 2001.
Mausel, P. W., Kamber, W. J. and Lee, J. K. (1990). Optimum Band Selection for Supervised Classification of Multispectral Data. *Photogrammetric Engineering & Remote Sensing,* 56(1):55-60.
McCready, M. and Hautaniemi, T. (2000), Exercise 3: Supervised Classification *http://www.geo.umass.edu/courses/geo591r/reports/ex3/group03/.* Department of Geoscience, University of Massachusetts, USA.
Mitri, G.H. and Gitas, I.Z. (2002). The development of an object-oriented classification model for operational burned area mapping on the Mediterranean island of Thasos using LANDSAT TM images. *Forest Fire Research & Wildland Fire Safety*, Viegas (ed.) Millpress, Rotterdam, ISBN 90-77017-72-0
USGS, 2003, Landsat 7 Science Data User Handbook
WANG, Q., 2001, Remote sensing and GIS evaluation of urban expansion and its impact on surface temperature in the Zhujiang Delta, China, *International Journal of Remote Sensing*, 22 (10):pp 1999-2003.

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Dr. Shattri has published over 150 articles in journals and conference proceedings. Dr. Shattri holds membership to various organizations and institutions. He is currently an executive committee for Malaysian Remote Sensing Society, an executive committee for the Institution of Surveyors Malaysia (LS Division), member of IEEE. He is currently the Editorial Board member of the Journal of the Malaysian Surveyor and Malaysian Journal of Remote Sensing and GIS.

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