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Land use/cover classification- An introduction review and comparison

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Abstract - Accurate and reliable information about land use and land cover is essential for change detection and monitoring of the specified area. It is also useful in the updating the geographical information about the area. Over the past decade, a significant amount of research has been conducted concerning the application of different classifier and image fusion technique in this area. In this paper, introductions to the land use and land cover classification techniques are given and the results from a number of different techniques are compared. It has been found that, in general fusion technique perform better than either conventional classifier or supervised/unsupervised classification.

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LAND USECOVER CLASSIFICATION- AN INTRODUCTION REVIEW AND COMPARISON

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Dr. Swapan Kumar Deb [α], Rajiv Kumar Nathr [Ω]

Abstract - Accurate and reliable information about land use and land cover is essential for change detection and monitoring of the specified area. It is also useful in the updating the geographical information about the area. Over the past decade, a significant amount of research has been conducted concerning the application of different classifier and image fusion technique in this area. In this paper, introductions to the land use and land cover classification techniques are given and the results from a number of different techniques are compared. It has been found that, in general fusion technique perform better than either conventional classifier or supervised/unsupervised classification.

Keywords : Land Cover. Land, Fusion, Multiresolution, supervised, unsupervised.

I. Introduction

Land-Cover/Land-use, being the new concept developing with the remote sensing technology, has become a crucial item of basic tasks in order to carry through a series of important works, such as the prediction of land-use change, prevention of nature disaster, management and plan land use, protection of environment, etc,. With the more thorough development of remote sensing technology and Geo-Analysis model, using remotely sensed data to monitor the status and dynamical change of land-cover/land-use is become the one of the one of the most rapid, credible and effectual method. Land-cover and Land-use are two different concepts in its intrinsic signification .Land-cover emphasize particularly on its nature properties and it is the synthetically reflection of various elements in global surface covered with natural body or manual construction. Using remote sensing classification method, whatever used or non-used covering object in surface can be separated. However, Land-use, emphasizing more on land's social properties, is the output of reconstruction activities that human adopts a serial of biologic, technologic measure to manage and regulate the land chronically and periodically according to determinate economic and social purpose. Thus, land-use is a process of turning natural ecosystem into social ecosystem, and the process is a complicated procedure by the synthetic effect from nature, economy and society. The manner, degree, structure, area distributing and benefit of land-use are not only affected by natural condition nut also restricted by diversified natural, economic and technologic condition, and in sometimes among all factors the social production form is determinant Land-use is the most direct and leading driving factor to the land-cover change. In carrying out research and application of the land-covert and land-use remote sensing investigation, the uniform classification system is usually built up by combining the two concepts under one system, which is called Remote Sensing Land-Cover/Land-Use classification system. There are various methods that have been developed to perform the Land-Cover/Land Classification particularly for multispectral and panchromatic imagery.

Satellite images are constituted by a set of measures of electromagnetic radiation. Each individual measure corresponds to an area unit (pixel) and a certain interval of wave-length (channel). Many projects have been carried out in the last years by national or international organizations as well as by private companies for making land cover maps or databases through photo-interpretation or automatic classification of satellite data. The most extensive use of remote sensing data is in the construction of land cover maps. In recent years, with the spread of Geographic Information Systems (GIS), databases rather than maps have been generally produced. Sometimes, some classes of adopted legends can be considered land use classes rather than land cover ones; therefore, many maps based on photo-interpretation of remote sensing data are called land cover/land use maps. CORINE land cover [1] is a relevant example of a land cover database created mainly on the basis of remote sensing data.

II. Land Use/Cover Classification

a) By Fusion

The power of data fusion based on statistics of thermal infrared images at 1 km resolution, resolution, with visible and near infrared images at 20-m resolution that better match the urban scale. The results demonstrate the capabilities of remote sensing to derive some components of the urban energy balance, and to monitor their spatial and temporal variability [2]. To extract rural human settlement, different agricultural cultivation types, urban and built up area with different construction density combination of optical and multi-temporal SAR data is quite simple compare to use anyone of them alone[3].

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Definiens eCognition was used to identify land cover types by examination of panchromatic data from different sources (SPOT and KOMPSAT-1), recorded at different spatial resolutions. The geospatial techniques is used for combining multi-concept image datasets, geospatial themes and population census data to study various surface features in the environs of Lahore district, the dynamics of urban expansion with reference to population growth, and analyze different population aspects with reference to the spatial distribution of urban and rural administrative units within the district. And also gives the information that which dataset have been found appropriate and effective for classification of land use/ land cover features [4]. EOS-MISR, Landsat-ETM+ and RadarSat-SAR are fused together to find out the effect of land cover and land use to carbon cycle and climate change modelling [5]. The Gaussian mixture classification and the multi-scale classification algorithm (SMAP) were used with different combination consisting of the SPOT image and the airborne multi-polarized SAR data (EMISAR), [6]. An ASTER sensor imagery, which was converted into top-of-atmosphere reflectance (TOA), was used to classify the land use/cover types, according to Co-ordination of Information on the Environment (CORINE) land cover nomenclature, for an area representing the heterogonous characteristics of eastern Mediterranean regions in Kahramanmaras, Turkey [7]. The Optical and SAR sensor data are co-registered for data fusion and classification process of five classes: crops, water, built-up, forest and grass Missouri [8]. The utility of radar is to accurately locate areas of natural vegetation, scattered agricultural, and settlements. Radar data were able to accurately map these features with approximately the same accuracy as TM [9]. Landsat TM and microwave data (contemporaneous image of the new radar sensor SIR-C/X-SAR) were combined through calculation of the principal components of the multidimensional data sets and a final classification was carried out and compared with the classifications obtained from optical and radar recordings separately [10]. The land use transformations are a result of the interaction of the biophysical drivers and human drivers. It applies the concept of the presence of an agent as the decision maker based on the information available to it at a particular point in time and space, in simulation the land use/cover changes [11].

Microwave land cover studies have been performed at high resolution with airborne, such as JPL AirSAR [12] and CCRS C/X SAR [13], and satellite SAR, and at global scale mainly with ERS-1/2 Wind scatterometer and the SSM/I. The potential of multi-frequency polarimetric SAR data in separating agricultural fields from other types of surfaces and in discriminating among classes of agricultural species has been demonstrated. Lee et al. exploited the land-use classification capabilities of fully polarimetric synthetic aperture radar (SAR) versus dual-polarization and single-polarization SAR for P-, L-, and C-Band frequencies. A variety of polarization combinations was investigated for application to crop and tree age classification. The authors found that L-Band fully polarimetric SAR data are best for crop classification, but that P-Band is best for forest age classification. This is because longer wavelength electromagnetic waves provide higher penetration. Moreover, the HH and VV phase difference is important for crop classification, but less important for tree age classification. Recent research addressed to urban areas by using multi-temporal analysis of SAR data, has demonstrated that the coarse resolution of ERS images does not prevent the possibility of characterizing these areas [14, 15]. [16] established the usefulness of multiple SAR views in road detection. Convenient indexes derived by the observed backscattering and brightness temperature from the ERS scatterometer and the SSM/I made it possible monitoring seasonal variations in various types of land surfaces [17],[18]. The combination of three bands of NDVI, daytime LST, and night time LST shows the highest accuracy. Three-band combination using only daytime shows lower accuracy than two bands using day and night time. Adding night time data obviously increases the accuracies of forest and built up classes. The night time data can well discriminate forest from active agriculture (or mature crops), deciduous forest in hot season from inactive agriculture (or non-mature crops), and built up from harvested or fellow agriculture [19].

b) Land use/cover classification

A supervised digital classification approach was adopted for the preparation of temporal crop and land use inventory. Cropping pattern analysis was carried out by GIS aided integration of temporal crop inventory information. In this process of matching land and use, all the constraints were examined and integrated with proper weight age according to their contribution and the possibility of making improvements considered [20]. The expert classification system is used to classify the dominant land cover types are cultivated vegetation (23%), high density urban (16%), cultivated land without vegetation (10%), and undeveloped (9%) [21] based on expert classification system earlier made by [22]for the Phoenix urban area using Landsat Thematic Mapper (TM) imagery. Two different classification methods were used: Unsupervised and supervised classification. Unsupervised classification is the identification of natural groups, or structures, within multispectral data. Supervised classification is the process of using training samples, samples of known identity to classify pixels of unknown identity [23]. This classification listing (Levels I-IV) reflects the detailed identification possible in depicting the land use, land cover and land forms [47]. With the employment of colour or false colour infrared aerial photography, a higher degree of accuracy, precision and detail can be realized. The recommended scale is 1:12,000 to 1:10,000 or larger for both the aerial photography and the graphics product (Handbook).

Descriptive and Correlation Analyses observed that while certain land use types are more generators of informal sector enterprises than others, there is a significant positive relationship between land use intensity and incidence of informal sector enterprises [24]. The authors implemented three new approaches to merging heterogeneous spatial datasets for change analysis: 1) we developed a 2000 satellite image ISODATA classification in a way that approximated the 1980 photo-interpreted classifications as closely as possible; 2) we used a third independent data set collected consistently across the two dates to constrain and improve the comparability of the classifications, and 3) we combined these in an allocation procedure. These approaches were integrated by a classification procedure that combined ISODATA clustering methods with a multi-objective land allocation procedure (MOLA), [25].

The domain concepts is used to build generic description of patterns in remote sensing images, and then use structural approaches to identify such patterns in images for detecting land use patterns in Amazonia from INPE's remote sensing image database [18].Wavelet based approach was used to detect the change in road network with the help of GIS [26]. The Neural Network (NN) classifier is tested with SPOT data for the classification [27]. The image processing system ERDAS Imagine and Idrisiw were used in processing and classifying the acquired images. Geo-referencing of images was executed on the basis of ground control points, derived from 1:100,000 scale topographical maps. An unsupervised classification of images was done first for identification of land use patterns grouping, and for grouth truthing for training site selection. A supervised classification of images was carried out using the maximum likelihood method. This decision rule is based on the probability that a pixel belongs to a particular class with the highest probability among several possibilities [28]. The comparative study of the use of unsupervised clustering algorithms for pre-classification of satellite images [29]. A decision tree classifier approach was used to extract knowledge from spatial data in the form of classification rules. The extracted knowledge was used for improving the classification accuracy. It also indicates that the knowledge extracted from this approach can solve the problem of spectral confusion to some extent. The results were compared with the maximum likelihood classification [30],[31]. A new region-merging segmentation technique was linked with this technique with the FAO Land Cover Land Use classification system resulted in the development of an automated, standardized classification methodology [32]. A multidimensional approach to classification can counteract this trend by decomposing the land into a set of fundamental and independent dimensions based on measurable characteristics which can then be used separately and in combination to provide a structured approach to classification. The approach offers the potential to develop a generic land-based classification capable of harmonizing different classification schemes and satisfying the requirements of different users. the standard maximum likelihood (ML) classifier with equal a prioris (only for the three channels case) and a special case of the ML classifier, considering proper distributions for SAR data, for the two polarimetric channels case 33],[34]. Any change in land use land cover increase the soil erosion[45] which leads to raising of the beds of rivers thus reducing their capacity and consequently spilling the flood waters in to adjoining areas, silting the reservoirs, loss of soil fertility etc. The multi-temporal ASAR imagery was first orthorectified using NTDB DEM and satellite orbital models. K Nearest neighbour (kNN) classifier was used to extract eleven land cover classes. Supervised and unsupervised classifications were performed with five training classes of water, dune, urban area, vegetation and saline soil [35]. PCA is used for the classification of SAR image ([36],[37]. The two approaches namely Van Zyl approach was used to classify the Lee filtered image pixels into three categories: (1) odd number of reflections, (2) even number of reflections, and (3) diffuse scattering and the Cloude and Pottier's target decomposition theorem was studied and employed to group all pixels into nine different zones (or nine classes) accordingly to the partitioning of the entropy (H)-alpha (x) plane. The decomposition is based on the eigen value analysis of the complex coherency matrix T, which is based on Pauli matrix representation [38], [46]. The land use sources and destination was analyzed by conversion matrix. The extent to which post-independence land use and land cover changes have influenced environmental degradation in the most environmentally sensitive sections of the Garhwal Himalayas in India, the Alaknanda Valley [39]. It reveals the trend of geographic changes and related changes in land use pattern of the estuarine island in response to the natural and anthropogenic activities [40]. It is generally recommended that a thresholding procedure be performed on the data, so that change and no-change pixels can be readily located in the change imagery. Thresholds are usually based on the number of standard deviations from the mean of the change image, typically an iterative and subjective procedure (41],[42]. Therefore, recent research has examined the selection of thresholds based on a sound statistical basis [43],[44].

III. Comparison of Various Results

Over the past decade, researchers have explored various methods which involved different fusion techniques and different classification algorithm of land use/cover classification of satellite images, few of them discussed here.

3.1 Land cover classification by combination of SAR and optical data Obviously, solely application of optical data as stated in previous paragraph enables to establish good land cover map, however, there are still some misclassification and the result needs to be refined for practical use. Combining analysis results of both optical and JERS-1 SAR we could obtain the best result.

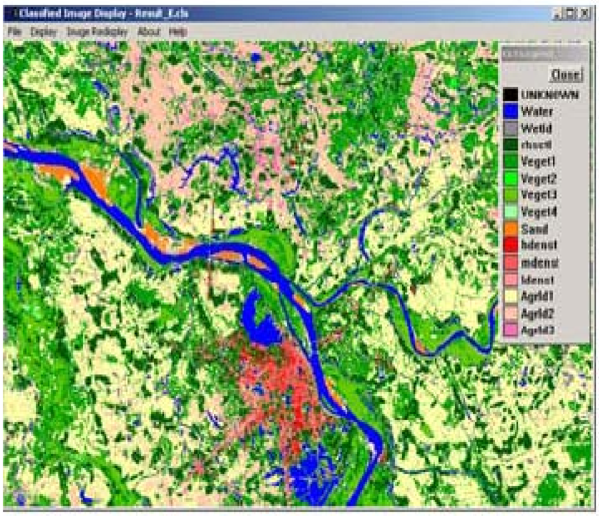
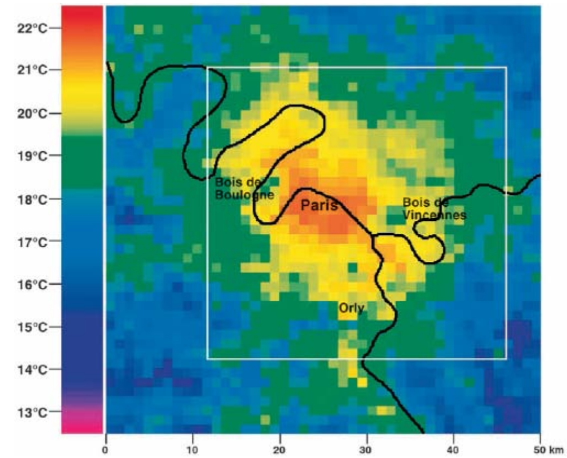


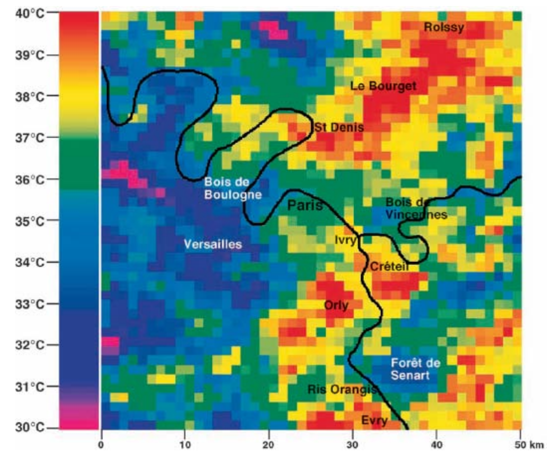
Figure 1 : Land cover map established by combination of optical and microwave data

3.2 Land evaluation may be defined as: "the process of assessment of land performance when the land is used for specified purposes"(Food and Agriculture Organization of the United Nations, 1985. The crop and other land use- land cover pattern of a region is an outcome of both natural and socio-economic factors and their utilization by man in time and space. Land is becoming a scarce commodity due to immense agricultural and demographic pressure. Hence, information on land use-land cover and possibilities for their optimal use is essential for the selection, planning and implementation of land uses schemes to meet the increasing demands for basic human needs and welfare. Increasing human interventions and unfavourable bioclimatic environment has led to transformation of large tracts of land into wastelands. Satellite remote sensing plays an important role in generating information about the latest land use-land cover pattern in an area and its temporal changes through times.

3.3 The land cover classification at 20-m resolution allows one to compute the percentage of a given class within 1-km resolution AVHRR pixels. Fig. 3a shows the percentage of the ''densely built'' class over Paris, and Fig. 3b displays its joint distribution with night and day average LST images. The night time distribution of LST is well correlated with the increasing density of buildings from the suburbs to downtown, as seen in Fig. 2a. The daytime distribution of LST also shows a correlation with density of building, although the variance is larger, presumably due to larger fluctuations of the heat fluxes, hence of LST, under the stronger radiative forcing conditions.



(a)



(b)

Figure 2 : Night time average image of Paris LST based on five NOAA-AVHRR thermal IR images at 03:27 UTC, August 6 –10, 1998.

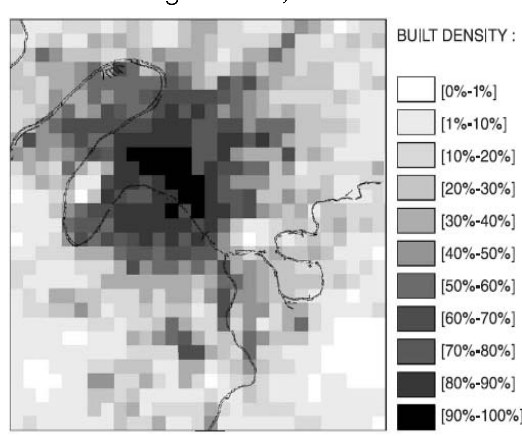


Figure 3 : (a) Percentage of densely built class (incl. roads) at 1-km resolution, derived from the 20-m resolution land cover classification of Paris. (b) Joint distribution of percentage of the densely built class, with night time and daytime average LST images (Fig. 2a and b).

3.4 Three different sensors (Landsat MSS, TM, ETM) image of Lahore City of Pakistan which is situated within the geographic extents of (74^0east to $74^0$39'23"east) longitude and (31^0 13'18"north to $31^0$43'north) latitude, the expanse of Lahore district encompasses an area of 1772sqkm. The higher levels of accuracies were achieved in case of Landsat MSS Image Dataset because that image contained more spectrally separable features than those were in the image datasets of the later dates. Difference in Spectral, spatial and radiometric resolutions of each datasets could also be one of the reasons for varying classification success rates. Diminishing vegetation can be observed in the direction of population expansion, the agricultural land is successively being converted into commercial/ residential areas for potential construction of houses, apartments and plazas. Moreover, as obvious from the classified image datasets, areas of sparse population convert into those of thick population over a period of 5-10 years. Hence transformation occurs from spacious to congested city environs and from rural agriculture land to urban residential/commercial land within the district.

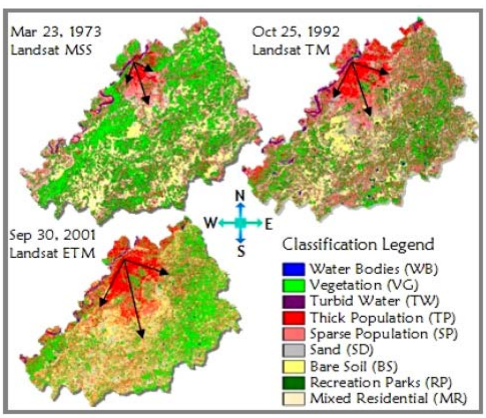


Figure 4 : Supervised image Classification showing Extent and Direction of Population Growth in the Study Area

3.5 A multi-spectral SPOT image, polarimetric airborne SAR data as well as satellite based C-band SAR data have been used to perform classification of agricultural fields and areas occupied by forest and lake with Conventional Maximum Likelihood classification and classification incorporating a Gaussian mixture class model, as well as an algorithm based on multi-resolution structured data and sequential MAP (SMAP).

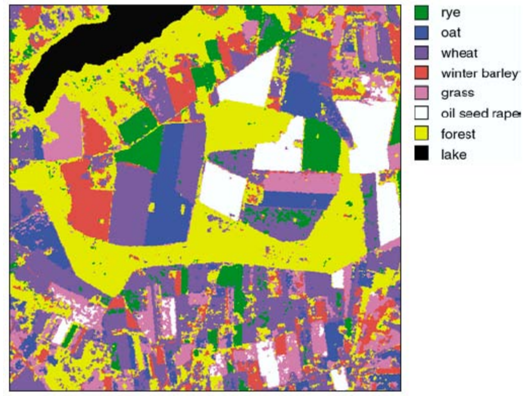


Figure 5 : Classified image based on the total data set Average accuracy is 95.9%.

Class	Label	pixels in training set	pixels in test set
1	rye	11535	12350
2	oat	21899	11709
3	wheat	31278	27983
4	winter barley	12358	12866
5	grass	10916	8753
6	oil seed rape	27942	27989
7	forest	24014	28336
8	lake	12723	11347

Table 1 : Number of pixels in training and test fields used in the classifications

The standard maximum likelihood (ML) classifier with equal priories (only for the three channels case) and a special case of the ML classifier, considering proper distributions for SAR data, for the two polarimetric channels case. The Support Vector Machine classifier (SVM) with Radial Basis Functions Kernel, was selected as the deterministic pixel based classifier representative. 3.6 Multisource and Multitemporall Data in Land Cover Classification Tasks: the Advantage Offered by Neural Networks

The experiment was carried out with different set of classes and multi-layer feed forward neural networks, trained by means of the Error Back Propagation algorithm with different numbers of internal, hidden and output neurons. the accuracy of the classification can be strongly increased, if four microwave images are available, as happens in mid July. The result is given below in the table:

Class	Commission (%)	Omission (%)
Grassland	31.13	34.74
Oat	60.43	47.77
Spring barley	66.32	69.07
Forest	76.62	78.05
Winter Barley	42.97	55.25
Winter Wheat	69.37	49.95
Moorland	67.07	78.38
Urban	75.51	62.82
Water	98.62	93.97
Overall (%)	66.73	

Table 2 : Classification accuracy (S3, June)

Class	Commission (%)	Omission (%)
Grassland	87.50	79.21
Oat	72.32	67.35
Spring barley	84.72	78.80
Forest	91.34	92.02
Winter Barley	84.83	70.12
Winter Wheat	71.61	84.09
Moorland	80.71	89.28
Urban	81.89	75.21
Water	96.04	95.28
Overall (%)	83.18	

Table 3 : Classification accuracy (S 1-S2-E1, May)

Class	Commission (%)	Omission (%)
Grassland	66.77	56.01
Oat	65.30	49.65
Spring barley	59.30	55.01
Forest	68.30	82.79
Winter Barley	58.74	41.05
Winter Wheat	64.39	71.16
Moorland	60.37	63.64
Urban	73.82	86.08
Water	99.33	92.04
Overall (%)	69.07	

Table 4 : Classification accuracy (E2-S3-E3, June)

Class	Commission (%)	Omission (%)
Grassland	78.48	78.68
Oat	88.03	70.79
Spring barley	80.70	88.63
Forest	90.02	91.15
Winter Barley	74.79	78.28
Winter Wheat	82.32	81.57
Moorland	86.74	82.29
Urban	80.19	83.87
Water	99.45	94.36
Overall (%)	84.58	

Table 5 : Classification accuracy (S2-EI-E2-S3-E3-E4, July)

3.6 The combination of unsupervised and supervised classification was used. In the land use classification generated using Arc View tools; the distribution of land use is the following: the predominant land use of the area is forest, followed by herbaceous rangeland, followed by agriculture, and a small portion of the watershed composed an urban area. In this classification the rangeland area that is located in the center of the watershed can not be observed.

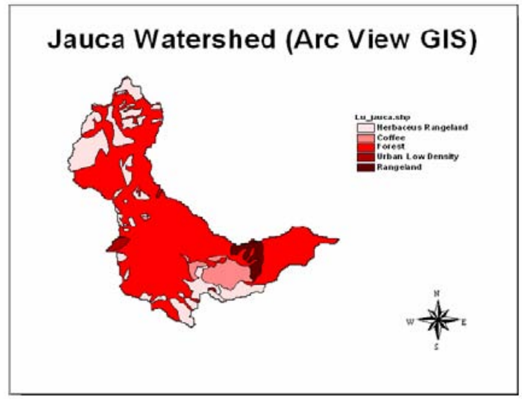


Figure 6 : Arc View GIS, Land Use Classification of Río Jauca

The procedure produced a final raster image with each pixel classified into a land-use class/cluster and each land-use class/cluster having the expected number of pixels determined from the NRI-LUDA relationship. Clusters were then aggregated to the desired output Level I land-cover categories. We used a sample of NAPP interpreted photos for validation. Results showed that the approaches we adopted in order to produce comparable classifications improved on AVHRR classifications alone.

3.7 The best kNN was achieved with combined Mean and Standard Deviation with multi-incidence angle, dual polarization eleven date ASAR images. ANN further improved the classification results of the textured images. As for comparison of classifiers, It was found that, with complex combinations (dual polarization, multi-incidence angle), ANN performs significantly better than kNN. The overall accuracy was 9.6% higher than that of kNN.

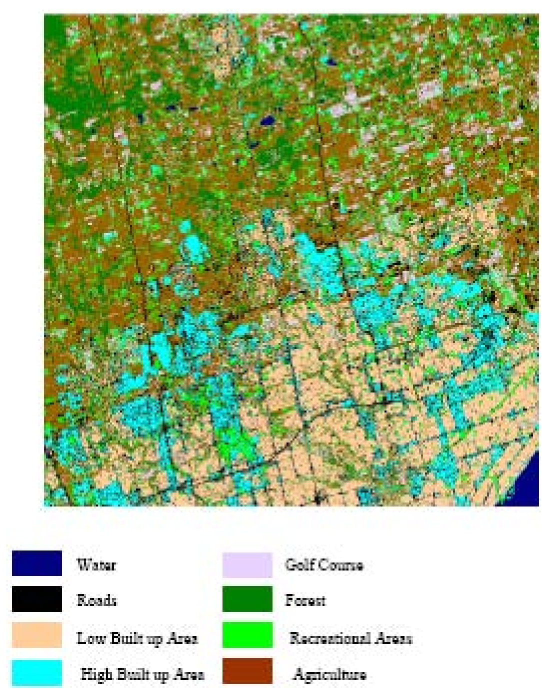


Figure 7 : Classified TM Images 1988

3.8 The Basic statistics index, fragmentation index, fractal dimension and diversity index was applied on the TM imagery of years 86, 96 and 2000 of the Haikou City. The 96 imagery was geo-rectified based on 1:100,000 DEM.

3.9 A principal component analysis was performed on a subset of the southern part of the Netherlands. In addition, the correlation coefficients between the 15 MERIS bands were mutually calculated. Subsequently, training samples for the main land cover classes were collected using the aggregated Dutch land cover data base as a reference. Per class two polygons of about 50 pixels each were identified in rather homogeneous areas. Thereafter the spectral signatures were studied. Finally, a minimum distance-to-means supervised classification was performed including clouds as a separate class in the training stage. In a post-processing step, the two subclasses per main cover class were merged.

The results of a minimum-distance-to-means (MDM) classification for the Netherlands, including also a class “clouds” in the training set. Classification accuracies were determined by using the whole land cover data base (Figure 2) as a reference. Table 5 shows the results for the main land cover classes (without classes bare soil and horticulture as indicated before). Results show a moderate overall classification accuracy of 49.7%.

3.10 After implementing all clustering procedures with the same initialisation conditions, we subtract the resulting clustering images from our reference image. The subtraction for each image was carried out by assigning the 9 clustering classes to the 5 reference classes and subtracting the clustered image from the classified image, pixel-by-pixel. As an example, Figure 8(a) shows the agglomerative hierarchical clustering result for 9 classes, and Fig. 2(b) the differenced image. The FMLE and AHC methods performed similarly well, with 11% and 10% discrepancies respectively in the differenced images. This is to be compared with 28% and 23% for the CM and FCM algorithms, respectively. We conclude that Fuzzy-Maximum-Likelihood and Agglomerative Hierarchical Clustering are superior to the more commonly-used C-Means and Fuzzy-C-Means Clustering for pre-classification analysis of LANDSAT satellite images. The problem of choosing the number of clusters remains a difficult one.

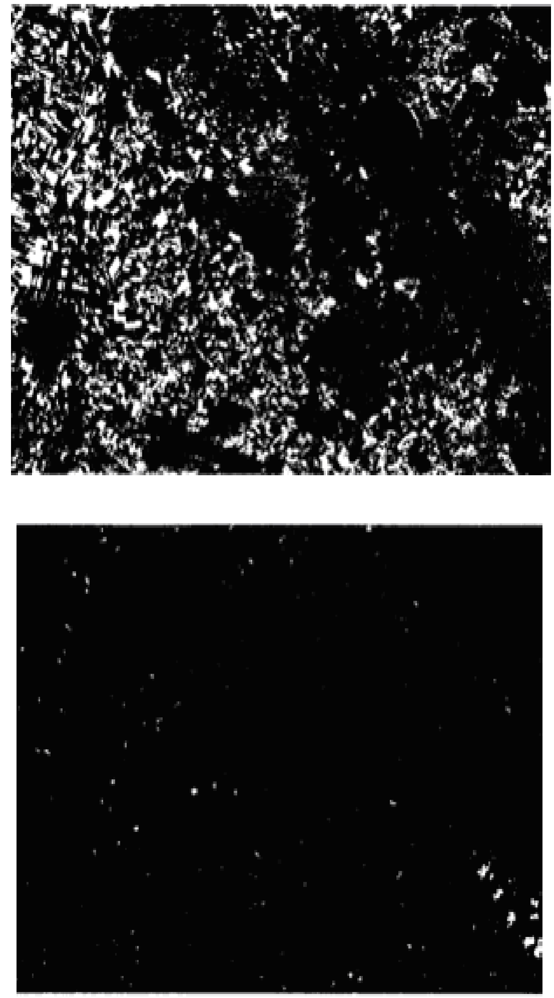


Figure 8 : (a) Classification result; (b) subtraction result

3.11 Road change detection and database updating based on wavelet and map conflation techniques was proposed for the satellite image of the 5.8 m IRS panchromatic image covering the urban area of Ottawa (ON, Canada).

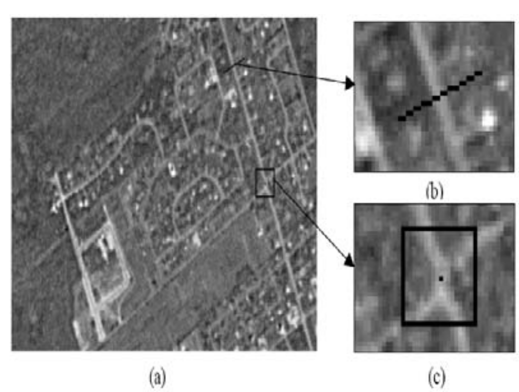


Figure 9 : Part of the IRS panchromatic image

Figure 10 : Road centerlines extracted from IRS pan image of urban area (red dashed line) superimposed with NTDB roads (green solid line)

IV. Conclusion

Generally, the accuracy of land cover classification depends on two factors. One is the amount of the spectral information provided by the input remotely sensed data, the other is the classification approach. For the same set of input remote sensing data, different classification approaches may have quite different accuracies. This is important because land cover and land use data products play an important role in quantitative modelling of carbon cycle and climate change. Input map accuracy is closely related to output uncertainties from these models.

Human error digitizing, lack of knowledge of study area, and other factors all contribute to inaccurate results in the supervised classification method. In any case, the resulting images are useful for some applications such as generating estimates on relative presence of water bodies, agricultural land use, and forested areas. If more accurate results are desired, additional processing to tease out specific land use patterns may be possible by detailed examination of the image and data. This technique requires more work and may not produce results that better represent what is actually present in the field. When using any classification technique, it is best to use additional references of the study area rather than only the satellite imagery. Without comparing these images to maps, aerial photographs, and actual visits to the study area, features actually present cannot be determined. The use of USGS Digital Line Graphs (DLG) (line map data in digital form) would be helpful in isolating out features such as asphalt and concrete. DLG hydrological maps contain information on transportation, flowing water, standing water, and wetlands further easing the job of classification. Also available from the USGS are Multi-resolution Land Classification (MRLC) maps. MRLC data are derived from Landsat 7 TM data. Landsat 7 TM has several advantages over pervious Landsat satellites including better resolution and an additional thermal band. These maps are available at reasonable price and already have land use classified into 21 different land use classes. The image fusion technique better result compare to conventional techniques because the in the cloudy season it works well compare to conventional method.

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Table 6 : Confusion matrix for supervised classification of TM 1988 image using kNN Classifier

Name	Water	Roads	LD	HD	Golf	Forest	Parks	Agriculture
Water	**100**	0	0	0	0	0	0	0
Roads	0	**93.8**	3.6	2.4	0	0	0	0.2
LD	0	17.4	**82.2**	0.5	0	0	0	0
HD	0	18.4	2.6	**79**	0	0	0	0.1
Golf	0	0	0	0	**80.6**	4.2	1.9	13.3
Forest	0	0	0	0	0	**100**	0	0
Parks	0	1.2	0.2	1.8	0	0	**96.8**	0
Agriculture	0	0.2	0	0	14.2	0	2.7	**82.9**

Average accuracy = 89.42%
Overall accuracy = 87.13%
Kappa Coefficient = 0.84345 Standard Deviation = 0.00409
Confidence Level:
99% 0.84345 +/- 0.01056
95% 0.84345 +/- 0.00802
90% 0.84345 +/- 0.00673

Table 7 : The landscape characteristics of land use change in the Haikou City

Year	1986				2000			
Land type	A_i	n	Pa	D	A_i	n	Pa	D
Cultivated	8178.86	30	272.63	1.302	5081.91	33	154.00	1.298
Forest	6474.92	43	150.58	1.328	5955.12	49	121.53	1.252
Grass	377.41	13	29.03	1.394	377.41	13	29.03	1.386
Water	2479.07	17	145.83	1.326	389.59	18	21.64	1.258
Urban	2805.21	19	147.64	1.296	8719.26	6	1453.21	1.212
Rural	253.31	19	13.33	1.273	493.34	23	21.45	1.285
Construction	1155.08	19	60.79	1.326	1755.14	20	87.76	1.390
Unused	950.92	5	190.18	1.258				

Table 8 : Results of a principal component analysis on a subset of the MERIS image of June 16th, 2003.

Principal component	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Explained variance /%	86.03	12.64	0.59	0.38	0.18	0.09	0.04	0.02	0.02	0.01	0.00	0.00	0.00	0.00	0.00

Table 9 : Correlation matrix for a subset of the MERIS image of June 16th, 2003.

r	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1														
2	.990	1													
3	.961	.990	1												
4	.944	.979	.996	1											
5	.860	.906	.938	.961	1										
6	.852	.907	.948	.969	.975	1									
7	.835	.891	.934	.954	.945	.993	1								
8	.831	.887	.932	.951	.941	.991	.999	1							
9	.632	.688	.735	.780	.914	.861	.824	.821	1						
10	-.011	.002	.010	.046	.261	.085	.009	.004	.515	1					
11	.054	.078	.096	.121	.302	.128	.043	.040	.497	.944	1				
12	-.069	-.061	-.057	-.019	.199	.025	-.047	-.052	.465	.994	.914	1			
13	-.087	-.079	-.075	-.034	.179	.007	-.064	-.068	.458	.990	.912	.997	1		
14	-.066	-.057	-.052	-.016	.198	.025	-.049	-.053	.471	.992	.930	.993	.998	1	
15	-.126	-.108	-.093	-.057	.157	-.013	-.087	-.091	.437	.980	.946	.977	.984	.989	1

Table 10 : Classification results for the MERIS image of June 16th, 2003.

	Producer's Accuracy	User's Accuracy
Grassland	35.2 %	61.2 %
Arable land	62.4 %	36.4 %
Deciduous forest	25.4 %	12.2 %
Coniferous forest	43.3 %	36.4 %
Natural vegetation	16.5 %	8.2 %
Built-up	24.4 %	51.3 %
Water	85.6 %	96.3 %
Overall Accuracy = 49.7 %		Kappa coefficient = 0.369

Table 11 : Results of classification into only 4 main classes for the MERIS image of June 16th, 2003.

	Producer's Accuracy	User's Accuracy
Agriculture	88.5 %	88.1 %
Forest	56.1 %	28.6 %
Built-up	24.4 %	51.3 %
Water	85.6 %	96.3 %
Overall Accuracy = 78.1 %		Kappa coefficient = 0.622