Landcover Mapping of Banda Aceh, Indonesia, using Optical and SAR Satellite Imagery

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ABSTRACT:

The fusion of optical and radar remote sensing data offers the opportunity to combine complementary sensors with different features. Most common application for image fusion is the classification, for example, the generation of a land use map. In case of radar data it is known to be difficult because of the speckle and variation in scattering. Nethertheless, in tropical regions most areas are cloud covered. Thus in this investigation it was checked how far a land use classification of the region of Banda Aceh (Indonesia) can be improved by the fusion of optical with SAR remote sensing data. In the first step it is attempted to investigate and analyse several methods of data fusion by using optical and SAR data in a pixel-based approach by additional knowledge-based information. In the second step it is intended, in an object-based approach also by using additional knowledge-based information, to accomplish the actual land use classification on the test area. In the third step the results have to be verified and improved by a local ground check. The end product is an updated analogue and digital land use map of Banda Aceh und region. The digital map is to be integrated in a Geographic Information System (GIS).

1. INTRODUCTION

On 26th December in 2004 at 1.58 Central European Time the *Sumatra-Andamanen Earthquake* hit with a magnitude of 9.0 the Indonesian Island Sumatra. The undersea earthquake caused a series of devastating water waves, so-called *Tsunami*, (jap.: *tsu* = Harbour, *nami* = Wave), which struck in addition to the Indonesian islands Sumatra also the coasts of Thailand, Malaysia, India, Sri Lanka and even East-Africa. The Tsunami-disaster damaged the city of Banda Aceh at Northern Sumatra very hard. In order to support the georisks management with respect to the sustainable reconstruction of settlement areas and geological questions in the Province Banda Aceh a land use map based on remote sensing data was produced using SPOT 5, ASTER and SAR data from RADARSAT and ENVISAT. The selected area covers about 26.85 x 25.5 km (Fig. 1, red square).

Fig. 1: Location of the test area

2. DATA AND PRE-PROCESSING

The used data set include two different acquisition times and different optical and SAR satellite data. The first set consists of a SPOT 5 scene (G, R, NIR and SWIR) acquired on May 23, 2005 and two RADARSAT scenes acquired April, 06 and January 24, 2005, which were mosaicked to cover the total investigation area (Fig. 2.1). The second data set consists of one ASTER scene (G, R, NIR, SWIR1, SWIR2 and TIR) and one ENVISAT ASAR scene also acquired January 25, 2005. The ASAR scene does not cover the whole area. A small part in the upper left corner of the scene is missing (Fig. 2.2).

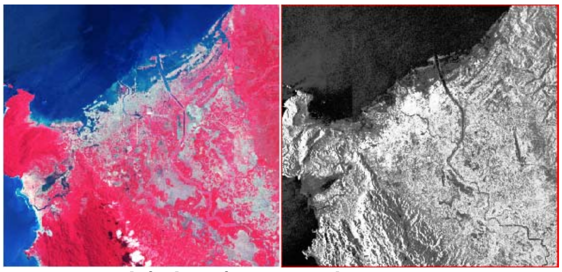

Figure 2.1: left: data of SPOT 5, right: RADARSAT scene

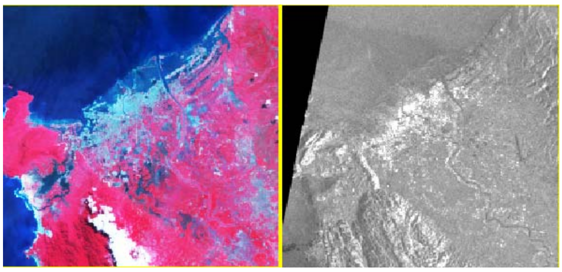

Figure 2.2: left: data of ASTER, right: ENVISAT

Optical and SAR data were georeferenced to each other by orthorectification. For the ASTER data a radiometric calibration had to be accomplished. In case of the SAR data a despeckling was performed by a Gamma-Map filter [1]. Afterwards the radar images were transformed to 8 bit in order to cover the same grey value range as in the optical data.

3. CLASS DEFINITION

For the final land use map all together 22 land cover and land use classes were defined according to a grouping into five main categories. The classes have been categorised by using a semantic (Tab. 3.1) and a spectral grouping (Tab. 3.2). This was done in order to achieve more representative and transferable results.

Agriculture	Soil	Urban	Vegetation	Water-bodies
Mixed Farming	Sand	Urban (dense)	Vegetation (dense)	Ocean
Paddy Farming	Gravel	Urban (sparse)	Vegetation (mixed)	River
Fish Farming	Limestone Mining	Urban (rebuilt)	Vegetation (sparse)	Flooding
	Clay Mining	Airport	Slash & Burn	Lake
		Industry		
		Military area		
		Parks		

Tab. 3.1: Categories and classes grouped semantically

Agriculture	Soil	Urban	Vegetation	Water-bodies
Mixed Farming	Sand	Urban (dense)	Vegetation (dense)	Ocean
Paddy (other)	Gravel	Urban (sparse)	Vegetation (mixed)	River
	Limestone Mining	Urban (rebuilt)	Vegetation (sparse)	Flooding
	Clay Mining	Airport	Slash & Burn	Lake
		Industry	Parks	Paddy (wet)
		Military area		Fish Farming
		Parks		

Tab. 3.2: Categories and classes grouped spectrally

4. PIXEL-BASED IMAGE FUSION AND CLASSIFICATION

Several pixel-based image fusion techniques have been tested in course of the selected classification approach, next the different fused data sets have been applied to the selected classification approach.

4.1 Classification Approach

The pixel-based classification approach is a combination of supervised and knowledge-based classification. Based on a supervised classification the results are improved by adding knowledge-based information. The rules for the knowledge-base are limited by boolean operations. In order to avoid an exceeding number of untagged pixel, their values were assigned to the class with the highest correlation or by applying further knowledge-rules. Thus some fuzzy logic was simulated in order to assign all pixel. For example, falsely classified urban areas in high mountainous areas were assigned to the category vegetation. Often urban areas are correlated with the class soil, but in this case also with vegetation because of the sparse settlement and the lack of visible soil in these areas. Knowledge-based rules such as values originating in DEM-Heights, NDVI-values and a ratio of the SWIR and NIR bands were used. For the five categories the following rules were estimated (Tab. 4.1).

	DEM Height [m]	Ratio NDVI [ ]	Ratio SWIR/NIR [ ]
Agriculture	< 100	> -0.1	-----
Soil	< 220	< 0.2	> 1
Urban	< 60	< 0.5	> 0.5
Vegetation	-----	> 0	-----
Waterbodies	< 60	< 0	< 1.4

Table 4.1: Rules of the knowledge-based classification

4.2 Fusion of the First data set (SPOT 5, RADARSAT)

Before multiple image sources are fused a reference data set of optical data was produced. The SPOT 5 bands of the first data set were used for this purpose. Many common image fusion techniques are known, like RGB band combinations, arithmetic combinations, colour-space transforms, statistical transforms and spatial transforms [2]. Out of these, two fusion techniques, namely the Multiplicative method (arithmetic combination) and the PCA Transform (statistical transform) were selected. Additionally the new Ehlers Fusion [3] was tested which is a combination of a colour-space transform and a spatial transform. The Ehlers Fusion showed the lowest colour distortions in comparison to the other methods. The Multiplicative method showed, as reported by other investigators [4], [5] the highest colour distortions (Fig 10.1).
For the accuracy assessment of the classification results 1000 reference patches of a size 3x3 pixel were taken from reference data consisting of aerial orthophotos and a local ground check.
The classification results of the fusion methods do not differ very much. The Multiplicative method offers the worst result of 84 %. The result of the PCA classification gives the best result (87 %) despite some colour distortions. The result of the Ehlers Fusion is almost similar to the result of the PCA. But in comparison to using only optical data (90 %) all three attempts indicate that no global nor local improvement could be obtained by image fusion.. Only the category waterbodies is almost similar to those of the reference data set (Fig. 10.2). The category soil is classified very bad in all fusion methods, because this category is highly correlated with urban areas. In this case the additional radar information even increases the correlation.

[%]	SPOT 5 reference	Multiplicative method	PCA Transform	Ehlers Fusion
Overall Accuracy	**90.2**	**84.5**	**86.8**	**86.2**

Table 4.2: Overall Accuracy of the pixel-based image fusion for the first data set

4.3 Image Fusion of ASTER and ENVISAT

As could be seen so far no global improvement could be obtained. One reason might be the inter-correlation of the categories. Another reason is the usage of data from different acquisition times. Thus it was tested in the second data set if the results could be improved by using data at same acquisition time. Therefore only the PCA Transform was chosen because this method offered the best classification result before. Because of the partly missing data in the Envisat scene the selected test area was reduced. Again the classification result is worse than the result using data of ASTER alone.

[%]	SPOT 5 reference	PCA Transform
Overall Accuracy	**79,9**	**77,3**

Table 4.3: Overall Accuracy of the pixel-based image fusion for the second data set

In order to decide if an improvement or a degradiation is of significance a test might be carried out, which is based on several independent classifications in order to obtain a distribution of classified results. For simplification the reference masks (patches) and their interior variance were analysed. Every patch offers nine classification having the value true or false. If all pixel are classified correctly the variance is very low. A single mis-classified pixel yields in a deviation of about 11 %. By comparing the difference of the mean values to the variance or standard deviation of both results a predication of significance can be made. Therefore the mean value and the standard deviation of all used reference masks were calculated. Table 4.4 shows that in case of the PCA Transform the standard deviation is higher than that of the optical ASTER data. But it can be seen that the standard deviation in comparison to the difference of both mean values is quite high in both methods. The variations of the classes are so high that no general statement on the adequateness of this test is feasible.

Waterbodies	Mean	Standard Deviation
ASTER reference	0.852	0.286
PCA Transform	0.784	0.331

Table 4.4: Mean and Standard deviation of the ASTER data set and the PCA Transform

5. OBJECT-BASED IMAGE FUSION AND CLASSIFICATION

5.1 Image Segmentation

Image segmentation is the first and important step in conducting object-based classification. Neighbouring pixels are grouped into homogenous image objects, which are defined by similar criteria such as colour and shape. The result of segmentation are image objects which can be classified in the next step.

5.2 Classification Approach

Again, a combination of supervised and knowledge-based classification was chosen. First a supervised classification with defined samples was started, by the so-called Nearest Neighbour method. Beside the mean value, which is the only known feature in the pixel-based approach standard deviation and ratio features were integrated. Knowledge was introduced as fuzzy rules for the single classes. For the 5 categories the knowledge-based rules of the pixel-based classification were adapted and partly refined to the single classes (except of a few very small classes like lakes, fish farming, clay mining, industry and military which were edited manually later). For the class river, as an example, the asymmetry shape was exploited. For potential land sliding in mountainous regions (sparse vegetation, slash and burn) the SWIR/NIR layer was used and refined. In case of paddy fields and airports a slope layer (slope is assumed to be 0), derived from a DEM, was computed. For the class soil, geological information was integrated by location features. Also class-related features were estimated. Flooding areas, gravel and former destructed urban areas are located near the class ocean in this test area. Also parks and sport fields are mostly near urban areas. A detailed description of the single knowledge-based rules is given by Schmitz [6].

5.3 Object-based Classification of SPOT 5 and RADARSAT

As reference the first classification performed only on the SPOT 5 data was used. In a second step the SPOT 5 and RADARSAT data were combined in the segmentation process. In a global Nearest Neighbour approach besides mean and standard deviation for all classes Haralick textures were integrated as new features from the RADARSAT data. Texture features were chosen because many objects and classes can be better described by textural characteristics in SAR images than using simple grey values. For the accuracy assessment of the classification results a reference mask consisting of several segments for every class and category was derived. The reference was computed as before, using orthophotos and ground check. The classification result of the fused data together with additional texture features again shows that no global improvement could be obtained compared to the reference data. The overall accuracy in contrary decreases about 1 % in case of the five main categories. For the category urban areas a slight improvement could be achieved.

In case of vegetation the degradation it is partly due to the mountainous areas which are either illuminated or shaded in the SAR image. Thus a lot of segments could not be classified. If the texture features are eliminated for the vegetation classes the overall classification result can be improved by 0.3 %. This is not much but visually recognizable (Fig. 10.4 and 10.5).

Confusion Matrix [Pixel]						
User \ Reference	Water-bodies	Vege-tation	Soil	Urban	Agri-culture	Sum
Waterbodies	8239887	33	95	50	143999	8384064
Vegetation	650	1717289	2267	41143	211011	1972360
Soil	1118	3694	123248	69983	5092	203135
Urban	36971	23135	42955	750959	130591	984611
Agriculture	76192	262138	10798	95924	2081789	2526841
Unclassified	7393	369	2336	3308	4067	17473
Sum	8362211	2006658	181699	961367	2576549	
Accuracy [ ]						
Producer	0.98537	0.85580	0.67831	0.78114	0.80798	
User	0.98280	0.87068	0.60673	0.76270	0.82387	
KIA Per Class	0.96387	0.83232	0.67360	0.76469	0.76601	
Total accuracy [ ]						
Overall Accuracy	0.917					
KIA	0.858					

Table 5.1: Confusion Matrix of the optical reference (SPOT 5)

Confusion Matrix [Pixel]						
User \ Reference	Water-bodies	Vege-tation	Soil	Urban	Agri-culture	Sum
Waterbodies	8235040	18	246	53	159469	8394826
Vegetation	1701	1649635	4925	30972	231887	1919120
Soil	828	4770	108120	36933	31078	181729
Urban	42575	25525	47362	785379	175813	1076654
Agriculture	61523	314024	13095	97392	1970942	2456976
Unclassified	20544	12686	7951	10638	7360	59179
Sum	8362211	2006658	181699	961367	2576549	
Accuracy [ ]						
Producer	0.98479	0.82208	0.59505	0.81694	0.76495	
User	0.98097	0.85958	0.59495	0.72946	0.80218	
KIA Per Class	0.96237	0.79402	0.58976	0.80179	0.71530	
Total accuracy [ ]						
Overall Accuracy	0.905					
KIA	0.839					

Table 5.2: Confusion Matrix of the object-based classification using the fusion of SPOT 5 / RADARSAT with additional texture features

A second data set was used to test if an improvement could be obtained with data of the same acquisition time. The same rules as above were used. The parameters according to the class-related features and the NDV-Index had to be adapted. Because of partly missing data texture features were excluded for the category vegetation and the class ocean. The results again show no global improvement.

Confusion Matrix [Pixel]						
User \ Reference	Water-bodies	Vege-tation	Soil	Urban	Agri-culture	Sum
Waterbodies	918538	112	1016	1122	24947	945735
Vegetation	514	160939	959	3445	45274	211131
Soil	801	379	10598	9329	93	21200
Urban	5491	4869	6158	75288	19418	111224
Agriculture	3562	55788	874	17190	196395	273809
Unclassified	2278	985	605	525	164	4557
Sum	931184	223072	20210	106899	286291	
Accuracy [ ]						
Producer	0.98642	0.72147	0.52439	0.70429	0.68599	
User	0.97124	0.76227	0.49991	0.67690	0.71727	
KIA Per Class	0.96577	0.67812	0.51787	0.68171	0.61955	
Total accuracy [ ]						
Overall Accuracy	0.869					
KIA	0.776					

Table 5.3: Confusion Matrix using ASTER

Confusion Matrix [Pixel]						
User \ Reference	Water-bodies	Vege-tation	Soil	Urban	Agri-culture	Sum
Waterbodies	916561	194	1300	799	23385	942239
Vegetation	835	147683	534	7048	61709	217809
Soil	1839	888	8623	10469	254	22073
Urban	5870	3949	6858	66767	4376	87820
Agriculture	3353	68124	1405	18051	195604	286537
Unclassified	2726	2234	1490	3765	963	11178
Sum	931184	223072	20210	106899	286291	
Accuracy [ ]						
Producer	0.98430	0.66204	0.42667	0.62458	0.68323	
User	0.97275	0.67804	0.39066	0.76027	0.68265	
KIA Per Class	0.96064	0.60751	0.41848	0.60230	0.61239	
Total accuracy [ ]						
Overall Accuracy	0.852					
KIA	0.747					

Table 5.4: Confusion Matrix using a fusion of ASTER and ENVISAT ASAR together with textural features

In this data set the segments are very small with respect to the number of pixels because the pixel size is quite large. Thus only a small distance can be considered for the calculation of the textural feature. Therefore a third classification was started without texture. Only the mean and the standard deviation of the ASAR scene were considered as additional features. Now the calculated results show that a global improvement could be obtained. The Overall accuracy could be increased with about 0.5 %. But this is still not much.

Confusion Matrix [Pixel]						
User \ Reference	Water-bodies	Vege-tation	Soil	Urban	Agri-culture	Sum
Waterbodies	919205	115	959	695	25208	946182
Vegetation	414	160052	665	5964	45434	212529
Soil	1871	590	11068	9504	262	23295
Urban	2753	4081	5496	71056	5796	89182
Agriculture	4095	56224	1098	15912	209195	286524
Unclassified	2846	2010	924	3768	396	9944
Sum	931184	223072	20210	106899	286291	
Accuracy [ ]						
Producer	0.98714	0.71749	0.54765	0.66470	0.73071	
User	0.97149	0.75308	0.47512	0.79675	0.73011	
KIA Per Class	0.96755	0.67318	0.54083	0.64448	0.67048	
Total accuracy [ ]						
Overall Accuracy	0.874					
KIA	0.785					

Table 5.5: Confusion Matrix using a fusion of ASTER and ENVISAT ASAR without textural features

6. FINAL LAND USE / LAND COVER MAP

Finally the land use / land cover map was produced. The first data set of SPOT 5 and Radarsat was used. In this case the radar features mean, standard deviation and texture were used only locally for the categories Urban, Soil and Waterbodies i.e. where an improvement might be possible. An improvement could only be obtained locally for the class Soil, but the accuracy of Urban got worse. This effect might be caused by the correlation in between these two categories. The absolute accuracy was the same with 91.5%. Additionally to this data set the thermal band of the ASTER scene was used to support the correct classification of the category Urban. An improvement by using this band was recognizable in the second data set. In order to achieve a thematic accuracy of about 90 % the data set was edited/corrected manually using information from the ground check. The final classification result was enhanced with text and vector information (Fig. 6).

7. CONCLUSION

In the pixel-based approach it could be shown that the selected image fusion techniques Multiplicative method, PCA Transform and Ehlers Fusion were not able to improve globally the classification result in comparison to the reference data generated from classification of SPOT 5 data alone. Neither a visual nor a statistical improvement could be observed. In case of the first data set it is obvious that the results are worse because of the different acquisition times. But also for identical acquisition times the results could not be enhanced. It has been shown with the first data set that the Principle Component Analysis and the Ehlers Fusion seem to offer a quite good fusion approach for optical and SAR data. In case of the Multiplicative method colour distortions and a degradation of the classification results could be observed.

The object-based approach has shown too, that no global improvement could be obtained using both optical data sets and additional SAR derived information. The use of texture features failed because of the relative small size of segments, especially in case of the second data set. However in this case the standard deviation feature offered a good alternative. Therefore in future it has to be investigated if this changes by the selection of larger segments or higher resolution SAR data like the TerraSAR-X.

Generally it can be said that the object-based approach in combination with a knowledge-based classification offers a valuable tool to integrate optical remote sensing data with radar remote sensing data.

8. ACKNOWLEDGEMENT

We appreciate the support of Mr. Dr. F. Kühn who opened this cooperation with the BGR and provided the satellite imagery as well as Mr. Hoffmann-Rothe and his colleagues in Banda Aceh who supported the ground check during that time.

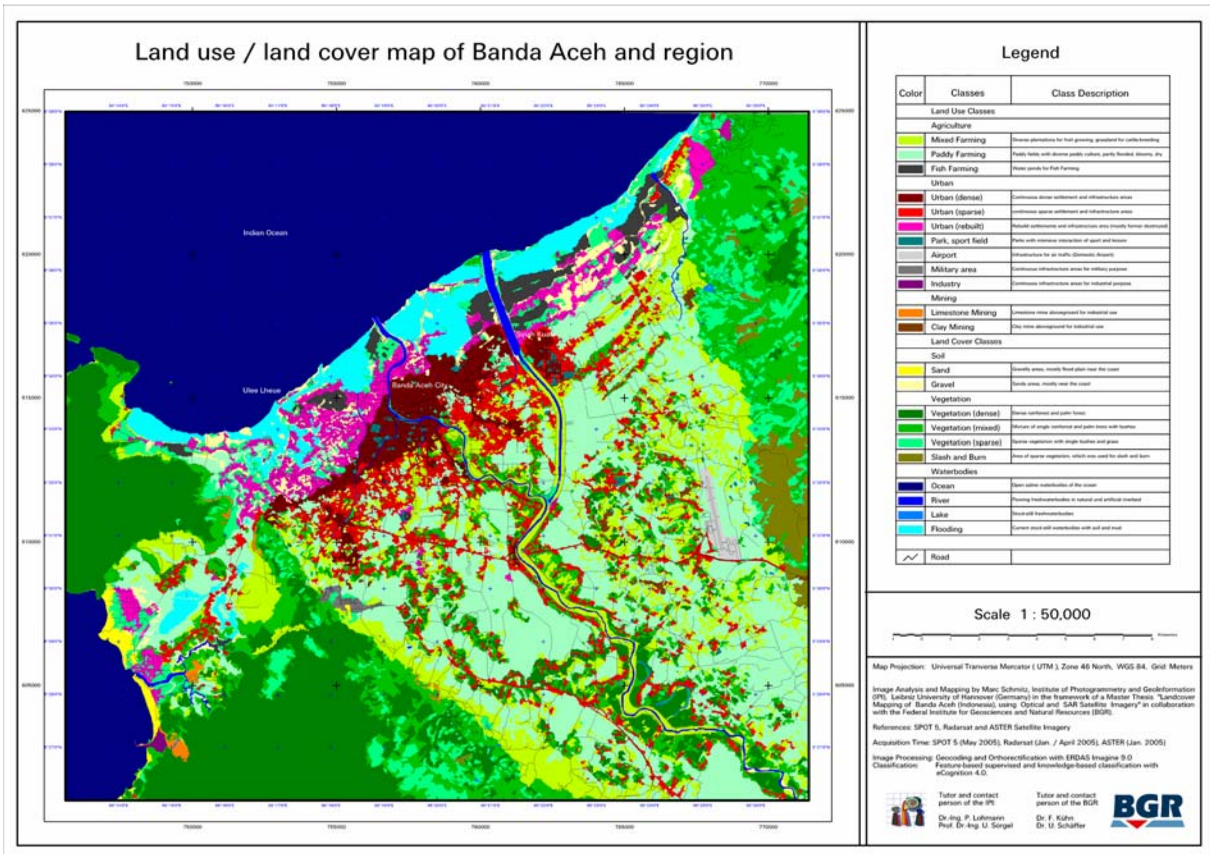

Fig. 6: Final land use / land cover map of Banda Aceh and region

9. REFERENCES

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10. ANNEX

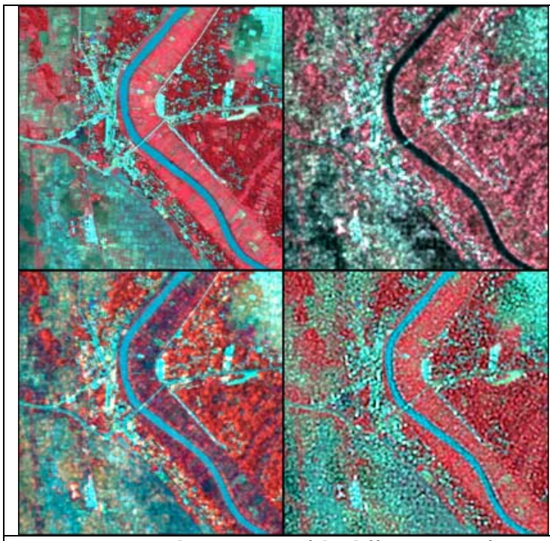

Figure 10.1: Visual comparison of the different image fusion methods in comparison to data of SPOT,
upper left: SPOT reference data set
upper right: Multiplicative method
lower left: PCA Transform
lower right: Ehlers Fusion

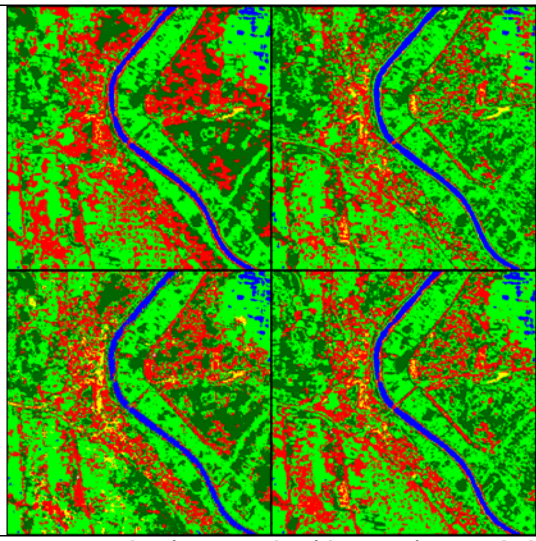

Figure 10.2: Classification results of the image fusion methods in comparison to data of SPOT,
upper left: SPOT reference data set
upper right: Multiplicative method
lower left: PCA Transform
lower right: Ehlers Fusion

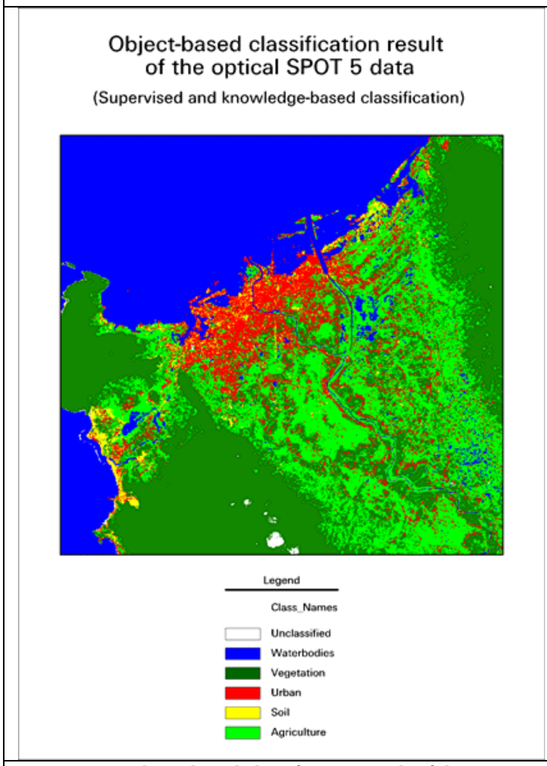

Figure 10.3: Object-based classification result of the SPOT 5 data by using supervised and knowledge-based classification

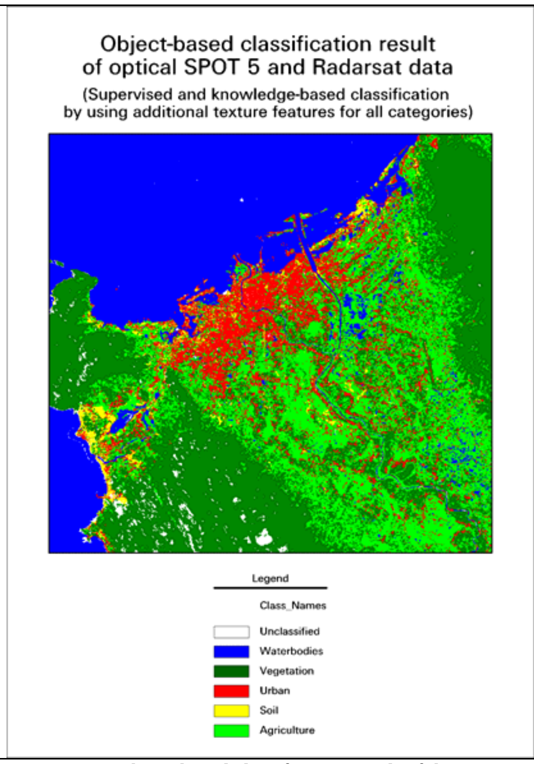

Figure 10.4: Object-based classification result of the SPOT 5 and RADARSAT data by using supervised and knowledge-based classification with additional textural features

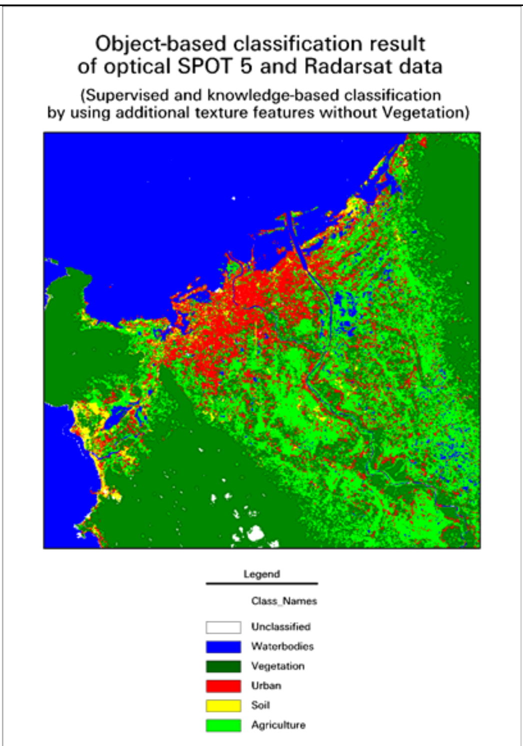

Figure 10.5: Feature-based classification result of the SPOT 5 and RADARSAT data by using supervised and knowledge-based classification with additional textural features without the category vegetation

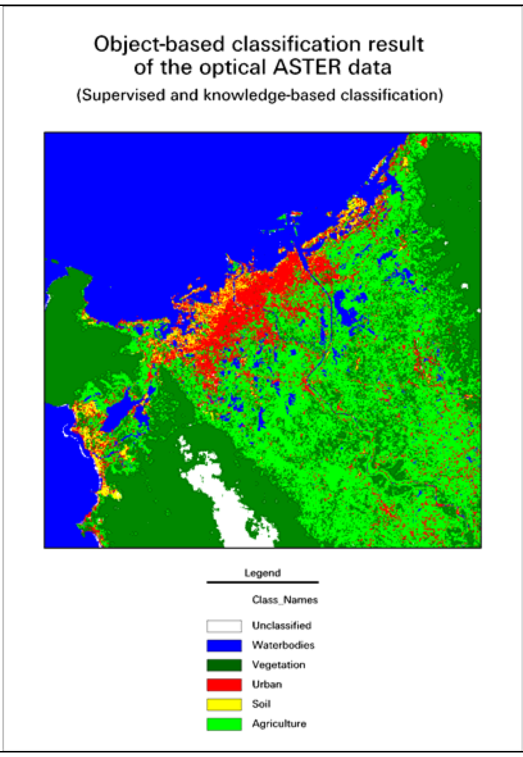

Figure 10.6: Feature-based classification result of the ASTER data by using supervised and knowledge-based classification

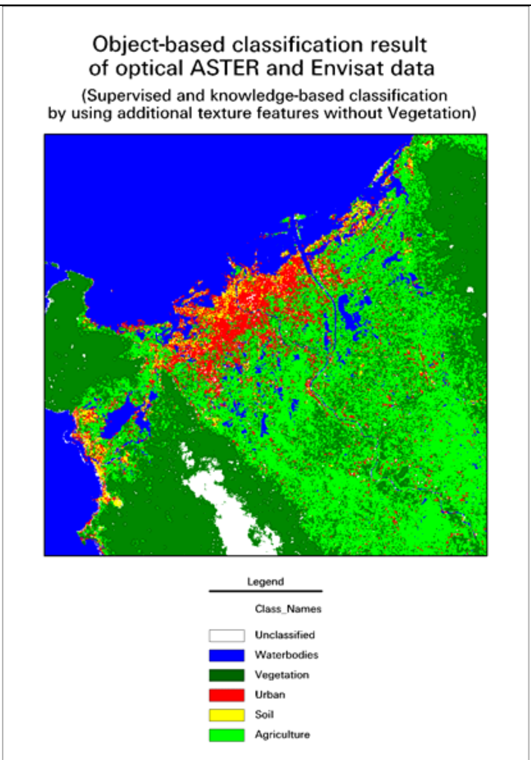

Figure 10.7: Feature-based classification result of the ASTER and ENVISAT data by using supervised and knowledge-based classifycation with additional texture features without the category vegetation and the class ocean