

# Comparison of object oriented classification techniques and standard image analysis for the use of change detection between SPOT multispectral satellite images and aerial photos.

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## ABSTRACT

The latest developments in remote sensing analysis software allow new ways of integrating satellite imagery with archive data from aerial photography. This paper shows how this integration is useful in a decision support function in forestry applications in the Argentine Nothofagus forests. Two important features are presented. One is the classification of SPOT multispectral data for determination of land cover in Tierra del Fuego. The other is the use of object-oriented classification for change detection using aerial photos combined with SPOT multispectral data. The until now critical objectivity of comparison was achieved by the methodological new approach of object-based classification. A basic description of the new concept of object-oriented classification is given, so far as it is necessary to understand its application in this study. The results for the SPOT data classification are that there are no great differences in accuracy of the two methods. Concerning the appearance of the output maps, the object-oriented method is preferred. The result for the change detection shows that the object-oriented approach offers new possibilities that exceeds the traditional visual interpretation of aerial photography and allows quantitative analysis of change detection and GIS-implementation using an automatic feature extraction.

## ZUSAMMENFASSUNG

Die neuesten Entwicklungen im Fernerkundungs- bzw. Bildanalysebereich ermöglichen neuartige Kombinationen von Satellitenbildern und Archivmaterial aus der Luftbildfotografie. Diese Arbeit zeigt, wie diese Kombination im Rahmen einer Entscheidungshilfe im Forstbereich für argentinische Nothofagus Wälder von Vorteil sein kann. Zwei wichtige Aspekte werden präsentiert. Der erste ist die Klassifizierung von SPOT Multispektraldaten zur Bestimmung der Bedeckungsformen in Feuerland, Argentinien. Der zweite Punkt befaßt sich mit der Quantifizierung von Änderungen innerhalb der Wald- Weidevegetation im Zeitraum 1960 bis 1995 unter Auswertung von SW Luftbildern und Daten des SPOT Satellitensystems. Die bisher kritische Objektivierung des Vergleichs wird durch den methodisch neuen Ansatz der Objektorientierten Klassifikation erreicht, mit welchem sowohl Luft- als auch Satellitenbilder ausgewertet wurden. Der verwendete Objektorientierte Ansatz wird soweit es zum Verständnis der Anwendung in dieser Arbeit nötig ist beschrieben. Zu den Ergebnissen der Klassifizierung der SPOT Daten läßt sich sagen, das es zu keinen großen Unterschieden betreffend der Genauigkeit gekommen ist, die Ergebnisbilder der Objektorientierten Klassifizierungen allerdings denen der Pixelbasierten vorzuziehen waren. Die Versuche im Bereich der Luftbild/SPOT Datenauswertung ergaben neue Möglichkeiten im Bereich der GIS Anbindung und change detection unter Anwendung einer automatischen Objektextraktion, die die bisherigen Möglichkeiten visueller Interpretation übersteigt.

## 1 INTRODUCTION

The temperate forest in Tierra del Fuego consists of two dominant species from the Nothofagus family. The glacial origin of the landscape and its history have made it possible to maintain a rather pure natural landscape with a relative modest impact from settlements in the post-Columbian period. His Situation is likely to change and modern tools and observation methods allow maintaining an overview, while simultaneously offering a discussion support system for the expected changes on a large scale in the near future. Of the 700.000 hectares of Nothofagus cool temperate forests that cover 30 percent of Tierra del Fuego only 50.000 hectares are exploited until now. This situation is likely to change within the next years for several reasons (CARABELLI 1999, J. BAVA, 1997):

1. Due to the rising population, the demand of timber in Tierra del Fuego has noticeably increased in recent years. Being a valuable hardwood, *Nothofagus Pumilio* could replace imports of Chilean *Pinus radiata*.
2. Lenga Patagonia, of the American timber company Trillium that owns 57.000 hectares of argentine *Nothofagus* forest plans the construction of a sawmill and fiberboard plant.
3. The owners of argentine sawmills want to expand their concession areas in order to be able to stay in competition.
4. Due to a cut in tax reductions by the argentine government, many foreign companies that were built in Ushuaia, the capital of Tierra del Fuego are closed. A sawmill could help reducing the increasing unemployment.

In spite of heavy resistance by national as well as international environmental organizations, it will not be possible to stop an increased exploitation of Argentine *Nothofagus* forests.

In order to assure the sustainability of the measures taken by timber companies, efficient and economic monitoring concepts are needed.

As a consequence the goal of this work done as a diploma thesis in 1999 was to make statements about the possibilities of change detection in the *Nothofagus* forests and to create monitoring concepts using the given data material.

## 2 DESCRIPTION OF THE STUDY AREA

As a test area for the examinations, an area of about 50.000 hectares was chosen. It is situated in the central part of the Argentine part of Tierra del Fuego between the 52° 30' S and 55° 30' S of the South American continent. The province capital Ushuaia claims to be the southernmost city in the world.

The area was chosen because specific studies were undertaken in this area during the PhD. thesis of Francisco A. Carabelli "Development of role models for a sustainable land use in Tierra del Fuego, Argentina".

All common forms of land use are found in this area as well as all of the important geomorphologic forms, soil types and vegetation forms.

The vegetation forms found are the two forest types *Nothofagus Antarctica* and *Nothofagus Pumilio* that are found mainly in the south of Tierra del Fuego and the grassland, situated mainly in the northern region where it forms the southernmost parts of the vast grasslands of the Patagonian pampas (P. FREDERIKSEN 1988).

Full coverage of satellite images as well as aerial photos was given. After two month of intensive ground-truthing work, enough information on the land cover and background information were gathered to start working on the image data.

## 3 DATA MATERIAL

The Material at hand was:

- SPOT multispectral scenes from 1995, covering the whole argentine part of Tierra del Fuego.
- Aerial Photos from 1960, covering most of the argentine part of Tierra del Fuego.
- A vegetation map, digitized from the aerial photos, covering about 50.000 ha of forest
- GIS data covering infrastructure, waterbodies, ownership and provincial as well as state boundaries

## 4 REMOTE SENSING DATA ANALYSIS

One aspect of the work was to study the separability of the two different *Nothofagus* forest classes and the non-forest classes. First statements had to be made concerning the separability of the spectral signatures of the three classes. Therefore the SPOT image was classified using standard as well as object oriented classification procedures.

For the change detection of the vegetation cover, datasets of the aerial photos combined with the three SPOT channels were produced and classified by means of object-based classification.

Approaches commonly used for photo interpretation are pixel-based classification and/or extraction of information by a human analyst. Those two approaches to image interpretation have their own roles and often these are complementary. Whereas human interaction is good for spatial assessment but poor for quantitative accuracy, computer aided quantitative analysis has poor spatial ability and high quantitative accuracy (RICHARDS & JIA 1998). As works by SCHNEIDER, LICHTENWALD & AMMER (1996) show, those are the critical points when assessing change detection problems by a combined aerial photograph / satellite data approach.

Using an object-based classification increases the computers spatial ability consequently making accurate computer aided photo interpretation possible.

## 5 METHODOLOGICAL APPROACH

### 5.1 Pixel based classification

For the pixel based classification standard maximum likelihood classifiers as featured by the software Imageworks developed by the Canadian company PCI Geomatics were used. The functionality of the pixel-based classification is not explained here in further detail and can be found in all standard literature (LILLESAND & KIEFER 1994, RICHARDS & JIA 1999, PCI REFERENCE MANUAL 1998).

### 5.2 Object based classification

The object-based classification was done using a Beta version of the software *eCognition* developed by the German company *Delphi2-Creative Technologies*.

*eCognition* is based on a new technology for object-oriented and multi-scale image analysis. Following an object-oriented approach, semantic image information that is not represented in single pixels, is made accessible.

The whole image analysis process can be divided into the two principal workflow steps, segmentation and classification.

#### Segmentation

Segmentation principally means the grouping of picture elements by certain criteria of homogeneity (HILDEBRANDT 1996). As the segmentation algorithm used by *eCognition* is not published yet, no specific information can be given. What can be told is that it is a kind of region merging segmentation process.

As the software classifies objects, not pixels, a first segmentation has to be made before the classification can be commenced. To get segments suited for the desired classification, the segmentation process can be manipulated by defining which of the loaded channel are to be used by what weight and by the following three parameters:

- Scale
- Color
- Form

The **scale** parameter is an abstract value with no direct correlation to the object size measured in pixel. It rather depends on the heterogeneity of the data material. The **color** parameter balances the color homogeneity of a segment on one hand and the homogeneity of shape on the other. A value of one on the color side will result in very fractal segments with low standard deviation of pixel values. A zero color value would result in very compact segments with higher color heterogeneity. The **form** parameter controls the form features of an object by simultaneously balancing the criteria for smoothness of the object border and the criteria for object compactness.

Using repeated segmentations with different parameters, a hierarchical network of sensible image objects is built (Figure 1). Each object “knows” its relationships to its neighbor-, sub- and super objects, which allows classification of relationships between objects. To ensure the hierarchical structure of the network, two rules are mandatory:

- Object borders of higher levels are inherited by the sub levels
- The segmentation process is restrained by super object borders

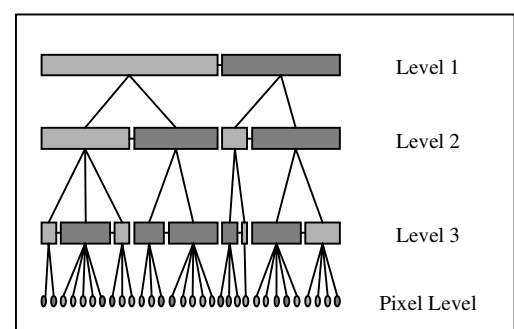


Figure 1: Hierarchical network of image objects

Supplementary to the normal segmentation two special types of segmentation are provided. One is the knowledge-based segmentation, the other the construction of sub-objects. The knowledge-based segmentation is a very important feature allowing the use of already made classifications as additional information for the merging of objects. Segments of one class can be fused on the same level or a higher level that then is constructed. The construction of sub-objects is used for special classification tasks like texture or form classifications based on sub-levels.

The segmentation process can principally be compared to the construction of a database with information of each image object. The classification process therefore can be seen as a database query.

## Classification

In order to be able to compare different object features like color and size as well as uncertain statements, fuzzy logic functions are used for classification (Figure 2). This allows classification of very complex tasks on one hand, and makes classification transparent and adjustable in detail on the other. Fuzzy logic is a mathematical approach to quantify uncertain statements. Basic idea is to replace the two strict logical statements 'yes' and 'no' by the continuous range of [0...1], where 0 means exactly no and 1 means exactly yes. All values or expressions between 0 and 1 represent a more or less certain state of yes and no. To translate the range of most different features into fuzzy logic expressions, the software uses two kinds of classifiers, membership functions and next neighbor classifier. All expressions of one class have to be combined to produce a result. This is done using logical operators such as **and** (**max**), **and** (**mean**), **or**, **if** and **else** (MAYER MECHLER SCHLINDWEIN WOLKE, 1993).

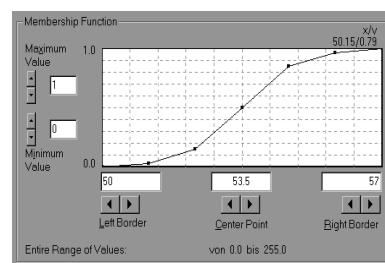


Figure 2: membership function

The features used for classification can be divided into three categories:

- Object Features like color, texture, form and area
- Classification related features like relations to sub-objects, super-objects and neighbor objects
- Terms like nearest neighbor classifier or similarity to other classes

## 6 RESULTS

### 6.1 Pixel based classification of the SPOT data

The first step was to analyze the separability of forest from non-forest as well as the two *Nothofagus* forest types using a maximum likelihood classifier without NULL class as featured in the *PCI ImageView* software. The following 4 classes were separated:

- Water
- Non-Forest
- *Nothofagus Pumilio*
- *Nothofagus Antarctica*

As one can see on the scatter plot, there are significant overlaps between the classes *Nothofagus Pumilio* and *Nothofagus Antarctica* as well as Non-Forest (Fig. 3). This is due to the strong inhomogeneity especially in the near infrared channel inherent to the two forest and the non-forest classes. This inhomogeneity is caused by the distribution of the pixel values in feature space, which is not normally distributed as expected by maximum likelihood classifiers. Table 1 shows the spectral mean values and standard deviation for the five classes. Given the small number of classes the classification result was nevertheless satisfactory. The confusion matrix based on the training areas (*not on independent test areas*) gave an average accuracy of 96.9% and a Total accuracy of 98.8% (LILLESAND & KIEFER 1994, RICHARDS & JIA, 1999).

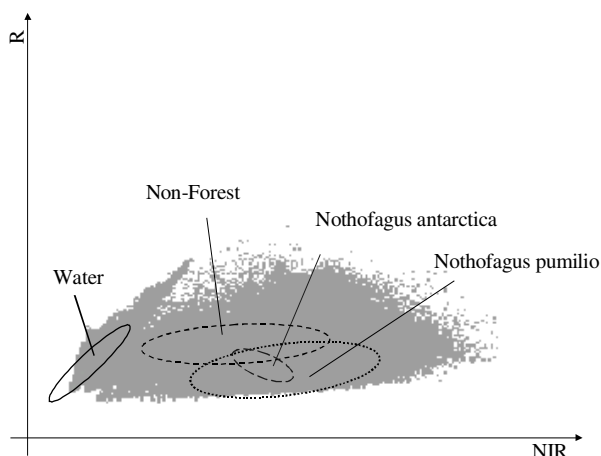


Figure 3: Scatter plot of the maximum likelihood classification with five classes.

Class	Channel	Mean	Std dev
Non-forest	Green	72,5	4,76
	Red	52,9	5,12
	NIR	77,0	17,72
N. Pumilio	Green	60,7	5,92
	Red	34,9	4,65
	NIR	95,9	17,82
N. Antarctica	Green	62,4	3,43
	Red	37,9	3,27
	NIR	87,4	5,83
Water	Green	62,4	3,43
	red	37,9	3,27
	NIR	87,4	5,83

Table 1: Spectral values of the different classes

## 6.2 Object based classification of the SPOT images

Additionally to the three SPOT channels used in the pixel-based classification, a fourth channel with an NDVI was used for classification. As in object-oriented classification also form, texture and other parameters were used for classification, the fact that the NDVI channel is derived from two SPOT channels poses no problems.

The Classification can be divided into three steps:

In the first step, a separation of water and non-water areas was achieved. For this purpose, a segmentation of solely the NDVI channel with a relatively high scale parameter of 25, so that large image objects resulted and form and compactness parameter of 0.2 each was made. The objects were classified using the spectral values of the NDVI channel and area parameter. The classified objects of each class were fused in a knowledge-based classification and the resulting objects were used as the highest object level (Figure 4 A).

In the next step, a second segmentation was made of the red and near infrared channel with a scale parameter of 15 and Form and compactness parameter of 0.3 each, producing objects suited for the separation of forest and non-forest. All objects with super objects of the non-water class were classified into forest and non-forest, using the nearest neighbor classifier in combination with training areas. The objects with super-objects belonging to the class water were also classified as water. The classified objects of each class were also fused building the second level of the class hierarchy (Figure 4 B).

The third and last step was to separate *N. Pumilio* and *N. Antarctica*. Another segmentation was made, using all three SPOT channels in combination with a low scale parameter of 5. The form criteria were set to 0.2, the compactness to 0.4. This time five classes were separated: Water, non-forest, non-forest II, *N. Pumilio* and *N. Antarctica*. Water and non-forest were classified according to their relation to their super objects. Non-forest II was used to correct the last classification of forest non-forest, so objects with super objects of forest, and specific spectral values were assigned to this class. The remaining two forest classes were divided using the relations to super objects and the nearest neighbor classifier. In addition, the class *Nothofagus Antarctica* had a border attribute, which denied objects to be classified as *N. Antarctica* if they were surrounded completely by objects of the class *N. Pumilio* (Figure 4 C).

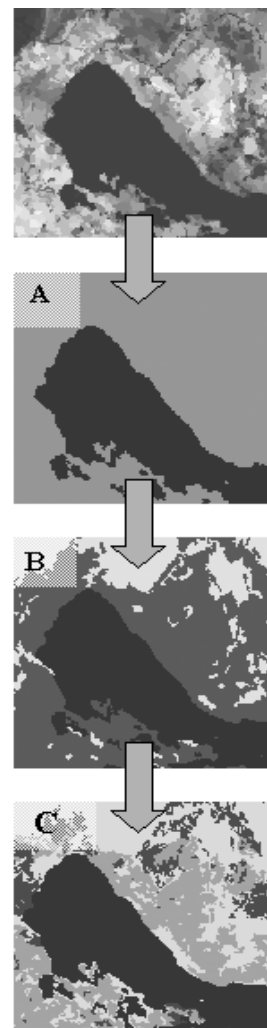


Figure 4: Samples of the different classification stages

## 6.3. Change detection with aerial photos and satellite images

### Image processing

The first concept to detect changes in the vegetation cover was to compare a vegetation map digitized manually from the aerial photos with the classification results of the satellite images. But by doing so, only statements about the changes that have occurred in just the small part, which was covered by the Map, could have been made. The software eCognition gave a method for change detection that was able to quickly produce accurate and reproducible information for nearly any spot on Tierra del Fuego.

First, the data material for classification had to be produced. The aerial photos were neither georectified nor information about the flying height or the lens focus was given. So the easiest way was to correct the scanned photos using the satellite images as master data. The Satellite images were then resampled over the SPOT data resulting in a pixel size of 2.5 meters. The results achieved were far from perfect but sufficient for the task.

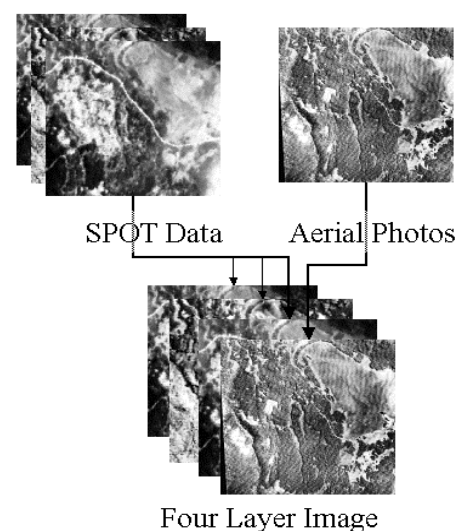


Figure 5: Samples of the different pre-processing stages

### Classification

The actual change detection is a quite straightforward process. A project with four layers, one being the aerial photos and the other three the satellite image channels is created and a first segmentation, which considers only the photo channel, is made. The parameters were a scale parameter of 70 and color and compactness parameter of 0.3. By using the nearest neighbor classifier containing spectral as well as texture and brightness features, the image objects were classified to forest and non-forest. The availability of the object variability makes this extraction of a forest mask much different from density slicing in a normal panchromatic imagery. The statistical parameters of the forest area encapsulate the textural information of the forest. This principle difference cannot be overstressed.

A second segmentation that uses the three SPOT channels provides the second level. The scale parameter was set to 15 and the Color and compactness parameters were set to 0.3 each. In this level all objects with super objects of forest and the spectral information of non-forest in the SPOT channels are classified as deforest classes and subsequently merged.

In the resulting level, a final classification was done, separating forest, non-forest and deforested areas. This time an additional size criterion was included in the classification, eliminating all deforest objects smaller than 800 pixels. So, the focus could be set to the objects of interest, the substantial changes in the forest vegetation.

The result is a map, which shows all major forest losses over the past sixty years. By varying the size parameter in the last classification, the scale of deforested areas that are of interest can be varied.

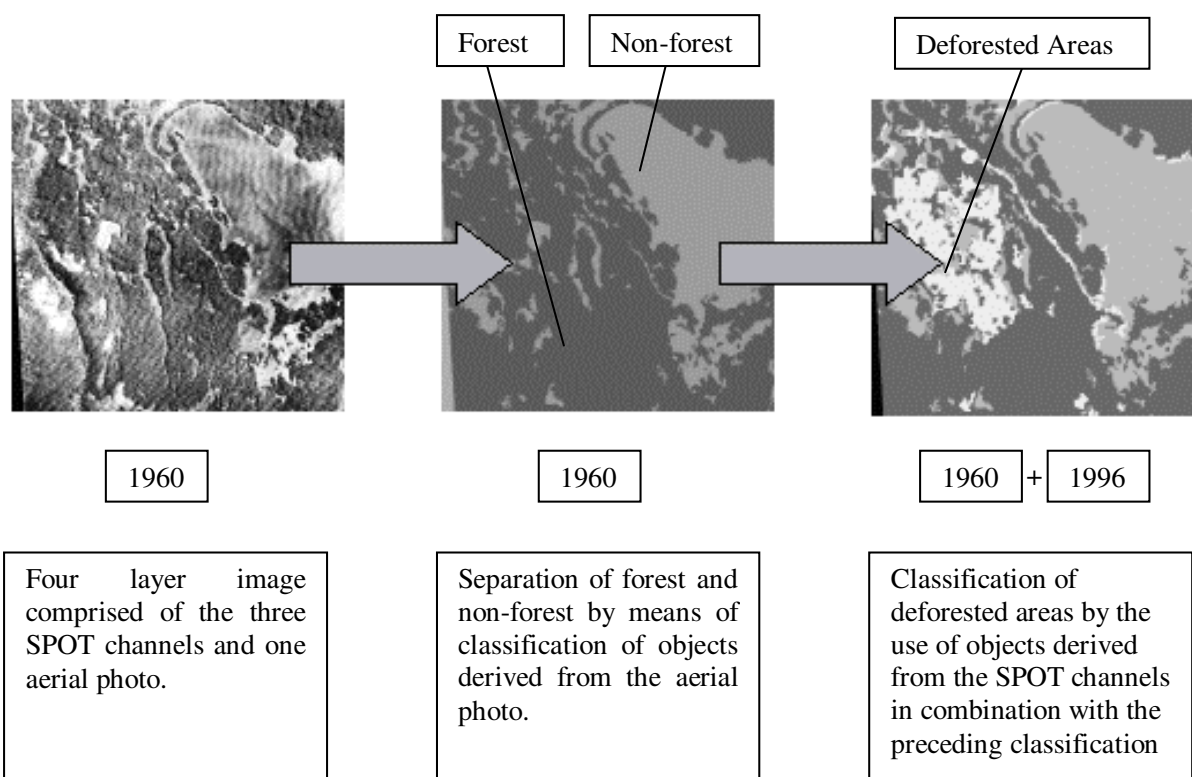


Figure 6: Aerial photo classification stages

### 7. DISCUSSION & CONCLUSION

The results of the pixel based and the object-oriented classification of the SPOT images were compared, using a set of test areas distributed randomly over the image. A confusion matrix was built, giving the pixel numbers of the test areas of each class and the percentages of correctly and wrong classified pixels of each class. As the result shows, (Tables 2 & 3) the classifications do not differ considerably. This could be due to the similarity of the classifiers used and the generally rather simple task.

Class	Pixel	Water	Non-forest	N. Pumilio	N. Antarctica
Water	1459	0,96	0,02	0,02	-
Non-forest	1606	0,01	0,94	0,05	-
N. Pumilio	2442	-	0,01	0,96	0,03
N. Antarctica	2617	-	0,03	0,17	0,80
<b>General Accuracy</b>					<b>90,95</b>
<b>Average Accuracy</b>					<b>93,21</b>

Table 2: Classification accuracy of the pixel based classification

Class	Pixel	Water	Non-forest	N. Pumilio	N. Antarctica
Water	1459	1,00	-	-	-
Non-forest	1606	-	0,97	-	0,03
N. Pumilio	2442	-	0,02	0,96	0,02
N. Antarctica	2617	-	0,08	0,05	0,87
<b>General accuracy</b>					<b>94,47</b>
<b>Average accuracy</b>					<b>96,09</b>

Table 3 Classification accuracy of the object oriented classification

What the confusion matrix does not show are the different appearances of the two classification results. Whereas the pixel-based map (Figure 6 B) shows a kind of salt & pepper effect with single pixels being distributed in the two forest classes, the object-based classification (Figure 6 A) rather resembles a manually digitized map. In this case the result of the object-oriented classification is preferred because it comes closer to the situation in the field. In reality, the two *Nothofagus* species do not build mixed stands so the small dots seen in the forest classes of the pixel-based classification are mostly misclassified pixels.

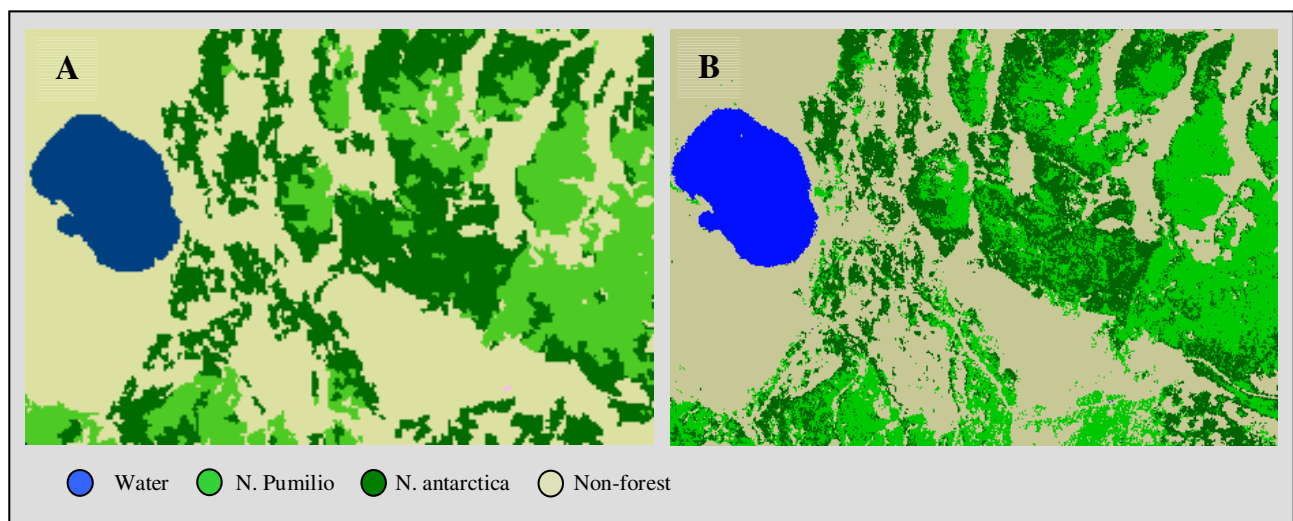


Figure 7: Results of object-oriented (A) and pixel-based (B) classification

The main advantage is that the object-oriented classification enables the export of Raster GIS layers established with attribute tables that can be filled with any kind of object information like class, area or texture. In the case of the classification of the SPOT images, this could provide the base for a very efficient monitoring system. Any new image data can be segmented, considering the information of the first classification. By doing so, no entirely new classification has to be made but instead the existing objects from the first classification are used with the new data. Any strong differences of one new object from the pixel values of the old one would indicate a change in this segment. This could simplify the whole working process by similarly making it more stable.

Concerning the change detection concept with the aerial photos it can be said, that with conventional classification processes it would be much harder if not impossible to realize. Using the protocol mode that is implemented in eCognition could make the automation of the biggest part of the process possible.

Not only in Tierra del Fuego archives with vast amounts of aerial photos can be found. This tool would make the evaluation of this data possible at a low cost and provide precious information.

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Descriptions of the segmentation and classification functionality of the software eCognition were partly taken from the *eCognition* beta version handbook and partly oral information received by the software developers of *Delphi2 Creative Technologies*.