Morphological Automatic Extraction of Pan-European Coastline from Landsat ETM+ images

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Abstract

Motivated by the need to generate a pan-European coastline database from Landsat 7 ETM+ images, we present a new methodology for extracting automatically the coastline and its application to the entire European continent. Our approach consists of the combination of spectral and spatial information for the images using morphological image segmentation techniques. For these purposes several morphological segmentation algorithms were implemeted inside a GIS platform to evaluate their performance in coastline extraction. The results demonstrate the accuracy of the developed methodology and its applicability to a large area such as the European continent.

1 Introduction

The delineation and extraction of coastlines and water bodies, e.g. rivers and lakes, is an important task useful for various application fields such as coastline erosion monitoring, coastal zone management, watershed definition, flood prediction, and the evaluation of water resources. This task is difficult, time consuming, and sometimes impossible for a huge region such as an entire continent, when using traditional ground survey techniques, because water bodies can be fast moving like in floods, tides, and storm surges or may be inaccessible. Tracing the coastline manually, although easy along relatively simple stretches of coast, is not practical where the coastline becomes very complex. In addition, automatic and replicable techniques are required to update coastline maps, to evaluate the spatial and temporal evolution of alterations due to natural and anthropic events, and to extract the waterline for large areas.

Following the growing availability of satellite images with increasing spatial and spectral resolution, the development of tools for geographic data analysis (GIS platforms) and image processing techniques, numerous research studies have been carried out to extract and delineate water bodies from these images [Smith, 1997]. The extraction of features, such as coastlines and water bodies directly from satellite images overcomes the problem of matching available coastline data sets with the studied image data set. In fact, owing to projection system biases, the matching of a coastline coming from a different data set together with the available images may turn out to be a tedious if not impossible task.

A scheme to detect shoreline changes using manual digitization of multi-temporal satellite images with tidal measurements and DEM was presented by Chen and Rau [1998]. Beyond manual digitization, several techniques have been reported in the literature for the derivation of the coastline position from satellite images [Smith, 1997], [Frazier and Page, 2000], [Ryu et al., 2002], and [Braud and Feng, 1998]. The most common are density slice using single or multiple bands and multi-spectral classification, both supervised and unsupervised (e.g. ISO-DATA, PCA, Tasseled Cap, NDWI).

These algorithms are based solely on spectral analysis of individual pixels without taking into account the texture, shape, morphology, and context of regions in the images [Whithe and El Asmar, 1999].

Frazier and Page [2000], present a large review of several approaches used by different authors to delineate water bodies from Landsat TM and MSS classification. They found that simple density slicing of the TM band 5 (mid-infrared) successfully detected lake/pond wetland areas, achieving a classification accuracy of the 96.9 percent, in the Wagga Wagga region of Australia, similar to the more complex methodologies (maximum-likelihood), but failed to extract small water bodies adequately. Simple Density slice of Landsat TM band 4 and band 7 give a good water classification result but with low accuracy respect to band 5. Braud and Feng [1998] evaluated threshold level slicing and multi-spectral classification techniques for detection and delineation of the Louisiana shoreline from 30 m resolution Landsat TM imagery. They found that thresholding TM band 5 was the most reliable methodology. Landsat TM or MSS classification using single density slice techniques represent a powerful automatic method to extract and map large water bodies such as lakes and coastlines.

Wang et al. [2003] investigated a novel approach for automatic extraction of shorelines from high-resolution IKONOS imagery using a mean shift segmentation algorithm as a first step, and then a local refinement process. A neural network classifier was used by Zhu [2001] upon multi-temporal Landsat images to classify the changes of coastline in different periods.

Extraction of waterline or coastline on specifically tidal flats has rarely been investigated in depth. The reflectance of flats tidal mud is affected by various parameters, including the particle size, the moisture content, the local slope, and the turbidity of seawater. Ryu et al. [2002] presented an approach to selecting an appropriate band or combination of bands to allow for the extraction of the waterline on tidal flat areas.

In genera, it appears that supervised classification techniques, based on spectral signature analysis, lead to good results in delineating and extracting large water boundaries from remote sensed data, but these methods meet some problems if the aim is to perform an automatic extraction methodology valid for a huge area such as a series of Landsat images covering a continent.

Motivated by the need to generate a pan-European coastline database from Landsat 7 ETM+ images, we present a new methodology for automatically extracting the coastline and lakes together with its application to the entire European continent. Our approach consists of the combination of spectral and spatial information for the images using morphological image segmentation techniques.

2 Methodology

The methodology developed here consists of automatically delineating the land/sea boundary using segmentation algorithms, that evaluate spectral and shape information of Landsat satellite images. The proposed methodology has four major components. The first consists of the extraction of Landsat images from the EC-image2000 DB using the SDE (ESRI) Raster engine. The second is the preprocessing and mosaicing procedure of extracted images pertaining to a specific region, e.g. nation or watershed. The third involves extracting coastline by using morphological image segmentation algorithms. The final step concerns the georeferentation, vectorisation and insertion of the coast boundaries into a GIS platform for JRC needs. A flowchart of the proposed scheme is shown in figure 1.

The segmentation algorithms implemented in C language are based on mathematical morphology operators. Mathematical Morphology (MM) [Matheron, 1967], [Serra, 1982] is a theory for the analysis of spatial structures and a powerful image technique also known

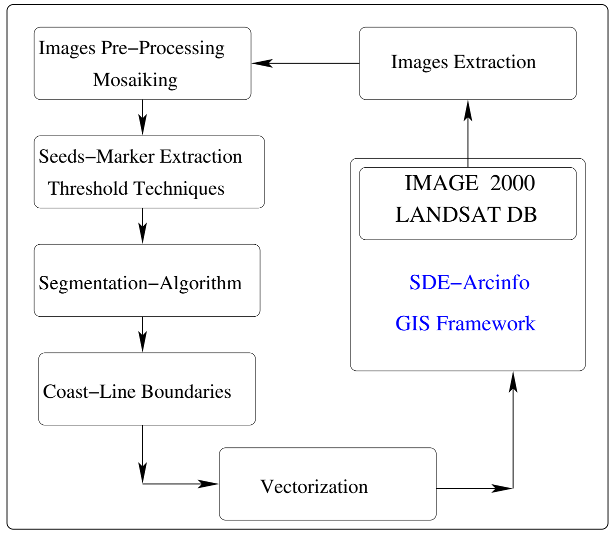

Figure 1: Flow chart of the methodology

as morphological image analysis. In MM, 2-D grey tone images are seen as 3-D sets by associating each image pixel with an elevation proportional to its intensity level. Another set of known shape and size, called the structuring element, is then used to investigate the morphology of the image. The MM approach for processing spatial data and image is well summarized by Serra [1988, p. 4]:"recognition of an object simply means that all the rest has been eliminated from the scene. This is a definitive irreversible operation". MM transformation and operators are therefore looking for objects defined as a specific spatial arrangement (shape, texture) of image pixels, rather than a single or cluster of pixels with a specific spectral signature (classification techniques). The delineation and extraction of objects from images through MM consists of the application of a sequence or chain of morphological operators aimed at iteratively suppressing all undesirable spatial structures occurring in the image. Image filtering and segmentation techniques based on MM transformations and operators permits the extraction of several objects by evaluating the shape and the texture of the image. Segmentation assumes that image objects are connected regions of rather homogeneous intensity levels. These assumptions allow for their automatic extraction by using a series of appropriate neighborhood properties.

2.1 Preprocessing

Pan-European Landsat satellite data were collected by EC-JRC inside a project called Image2000, in order to update the European Corine Land Cover database. Image2000 is a national and European multi-purpose, multi-scale, and multi-user mosaic, produced to satisfy national and European requirements for spatial analysis and environmental information. Image2000 images were produced from ETM+ Landsat 7 satellite, providing both multi-spectral (25 m resolution) and panchromatic data (12.5 m resolution). The images were delivered already ortho-rectified in national projection systems, then resampled using the cubic convolution and collected during the reference year 2000 with a deviation of maximum 1-year (1999 or 2001). The preprocessing procedures consist of extracting the Landsat images pertaining to the region of interest, e.g. nation state or regions, using the ArcSDE Raster Engine (ESRI) from the JRC Image Oracle DB and mosaicing them in a specific projection system. The mosaicing procedure was build inside a GIS (Arcinfo) platform working on a UNIX server station. The mosaicing algorithm developed permits the removal of clouds and areas of shadows from overlapping image regions, if one of the

Figure 2: Mosaic of pan-Europe Landsat 7 Images (± 15 Gb per multispectral band)

available images is cloud free. The algorithm to extract clouds and shadows regions is based on morphological image analysis algorithms.

2.2 Segmentation

The segmentation of an image can be defined as its partition into different regions (image objects), each characterized by certain properties. For grey level images the individual objects or regions in the segmented image are constituted by connected pixels of similar value or homogeneous grey level intensities. From the mathematical point of view, a segmentation of an image f is a partition of its domain $\mathcal{D}_f$ into n disjoint nonempty sets $X_1, X_2, ..., X_n$ called segments such that the union of all segments equals $\mathcal{D}_f$ [Soille, 2003a]. The algorithm for segmenting an image into meaningful regions requires some prior knowledge about the image objects that are to be recognized.

For our scope, we tested two different morphological segmentation algorithm. The first is a modified version of the Seeded Region Growing (SRG) algorithm initially proposed by Adams and Bischof [1994] and later enhanced by Mehnert and Jackway [1997] to achieve independence on the order in which pixels are processed. SRG is based on the postulate of region growing algorithms, where a criteria of similarity of pixels is applied, but the mechanism of region growing is similar to the morphological watershed algorithm [Meyer and Beucher, 1990]. Instead of controlling region growing by tuning homogeneity parameters, SRG is controlled by choosing a small number of pixels, called seeds. It starts with the selection (manual or automatic) of a number of seed regions $R_1, R_2, \ldots, R_n$ to which a region growing technique is applied. At each step, the algorithm proceeds by adding one unassigned pixel to one of the above sets until there are no more unassigned pixels in the image. This algorithm can be formally explained as follows. Let $N(\mathbf{x})$ denote the set of immediate neighbors of the pixel $\mathbf{x}$, and T the set of yet unallocated pixels which border at least one of the regions. That is, T corresponds to the external morphological gradient ρ^+ of the union of all R_i [Rivest et al., 1993]:

$$T = \rho_B^+(R). \tag{1}$$

where $R = \bigcup_{i=1}^{n} R_i$. The neighbour set B is defined as a 3×3 square structuring element.

If, for any pixel $\mathbf{x} \in T$, the dissimilarity d between $\mathbf{x}$ and R_i can be defined as follows:

$$d(\mathbf{x}, R_i) = \begin{cases} |f(\mathbf{x}) - \text{mean}_{y \in R_i}\{f(y)\}|, \text{ if } \mathbf{x} \in \rho_B^+(R_i), \\ +\infty, \text{ otherwise.} \end{cases} \tag{2}$$

where $f(\mathbf{x})$ is the grey level value of the pixel $\mathbf{x}$. Since a given pixel of T may border more than one region, we define the dissimilarity between this pixel and the set of all regions as the minimum dissimilarity between this pixel and all regions:

$$d(\mathbf{x}, R) = \min_i d(\mathbf{x}, R_i). \tag{3}$$

In each iteration of SRG algorithm we assign the pixels of T which have the minimum dissimilarity to their corresponding region. That is, all pixels $\mathbf{z}$ of T such that $d(\mathbf{z}, R) = \min_{\mathbf{x} \in T}\{d(\mathbf{x}, R)\}$ are appended to their correponding R_i. We proceed until all image pixels have been assigned to a region. The algorithm produces a tessellation of the image into the same number of regions, as those given by the seed regions. The boundaries of each homogeneous region are extracted by determining the boundary of the corresponding region using a morphological gradient function. In order to better evaluate the performance of SRG algorithm in coastline extraction from satellite images, we applied different combination of seed regions criteria (using multiple band) with different SRG algorithm versions. A modified version of the SRG algorithm, called SRGcore, differs from the original version in distance evaluation from pixel and region, in fact it computes distance between pixels along the external boundary of the already grown regions and the pixels of the original seeds which grew up to the internal boundary of these already grown regions. A SRG growing algorithm for multiple band and for morphological gradient (SRG GRAD) were performed and tested for coastline extraction from Landsat images.

The second algorithm is based on the watershed transformation (WS) using a marker-controlled segmentation procedure. The watershed transformation provides a clustering around the image minima. The image grey tone is viewed as a topographic surface slowly immerged into water. Starting from the minima at the lowest altitude, the water will progressively flood the catchment basins of the image. In addition dams are raised at the places where the waters coming from two different minima would merge. At the end of the flooding procedure each minimum is surrounded by dams delineating the boundaries of catchment basins [Vincent and Soille, 1991]. The definition of watershed in terms of flooding process is well suited to their efficient computation. Due to a one-to-one correspondence between the number of minima of a image and its number of segmented objects it follows that the watershed segmentation return and oversegmentation if applied to the raw image in the presence of spurious minima. In order to overcome this problem, and for our goals consisting in obtaining only two segmented objects, one for sea/water regions and the second for soil/land, we filtered the image using a marker minima imposition technique. The basic idea behind the marker-controlled segmentation is to transform the input image in such a way that the watershed of the transformed image corresponds to meaningful object boundaries. The technique for filtering the image is the minima imposition and is based on morphological reconstruction algorithm [Meyer and Beucher, 1990]. As explained the WS algorithm requires the determination of a marker function marking the relevant objects extracted using some feature detectors. The schematic illustration of marker-controlled segmentation is summarized in figure 3. The minima imposition detected by marker regions is applied to a segmentation function that enhances object boundaries, in our case we chose the morphological gradient.

Both SRG and WS segmentation algorithms require the identification of seed or marker regions. Rather than letting the user defining these regions, complete automation is achieved using a simple method of extraction for seed and marker regions, such as threshold techniques, and using the result of the first segmentation as a starting point for SRG or WS. In our case, each seed and marker regions belongs to either sea/water or land/soil. These regions were identified automatically on multispectral and panchromatic Landsat images

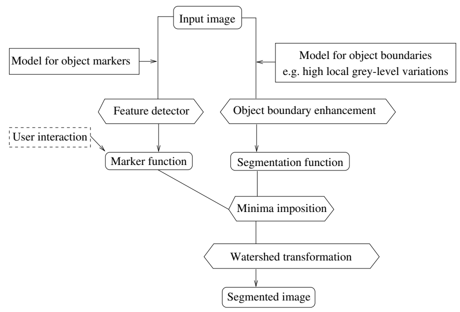

Figure 3: Flow chart for watershed marker-controlled image segmentation procedure, from [Soille, 2003b]

Table 1: Threshold values used in seed and marker regions for land and sea.

Slice Density	Water/Sea	Land/Soil
Band5	1-12	101-255
Pan	1-20	70-255
Band7	1-12	81-255
NDWI35	0.4-0.47	-0.25 - -0.1

using a simple density slice (threshold techniques) on single or multiple (NDWI) bands [Frazier and Page, 2000], [Braud and Feng, 1998]. The threshold values for extracting land and sea/water seeds were derived empirically on test images and they remain valid for the entire area of interest. Table 1 shows a list of threshold values used for automatic seed and marker region extraction for different bands and NDWI. The main requirement for identifying seeds and markers, consists of the delineation of representative pixels for each class without including noisy pixels wich can invalidate the seeded region growth and the marker segmentation procedure.

The results of each step in coastline delineation using the SRG and WS morphological segmentation on Landsat multispectral and pan bands are reported in figures 4 and 5.

(a) (b) (c)

Figure 4: a- Seed regions (land=red and sea=blue) on band 5, b- Region growing on band 5, c- Coastline

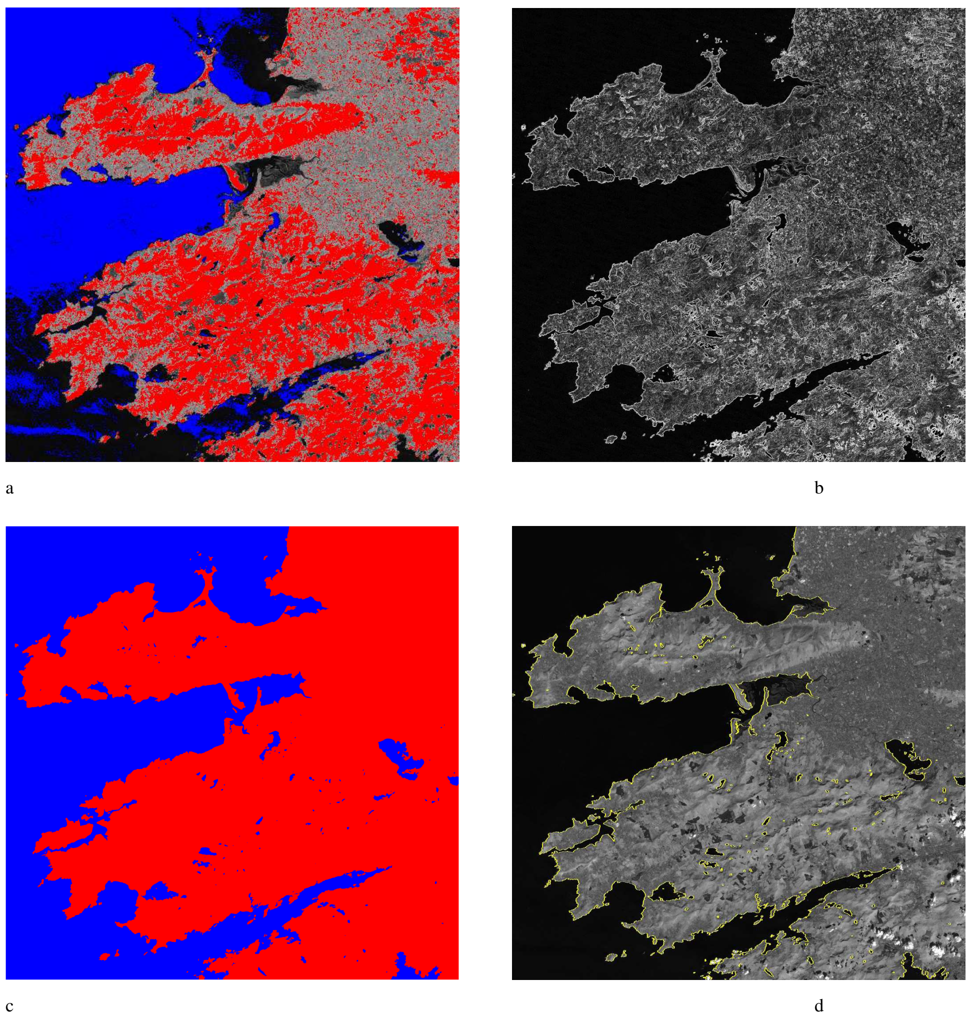

Figure 5: a- Marker function on band 5 (land=red and sea=blue), b- Segmentation function: Gradient, c- Watershed segmentation on band 5, d- Coastline.

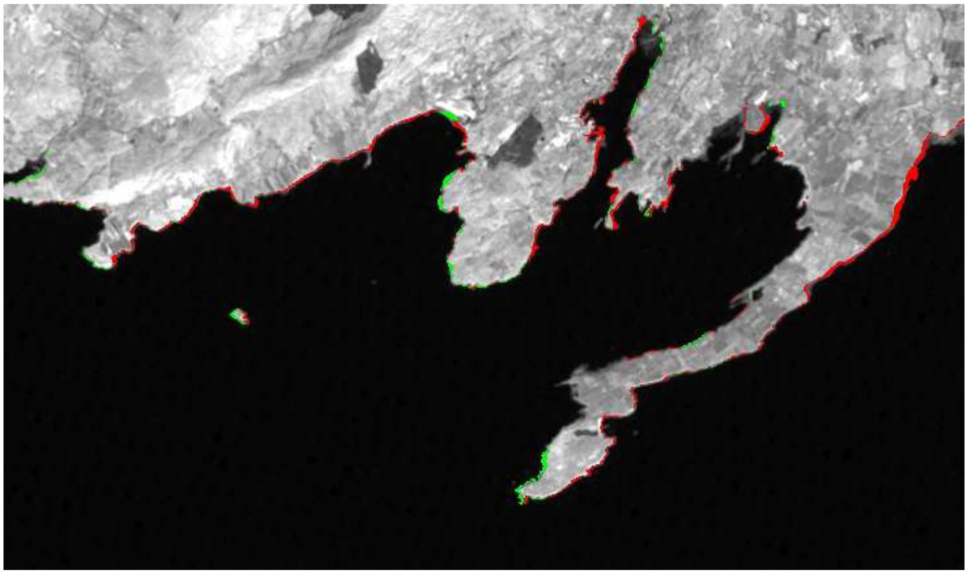

Figure 6: Discrepancies between extracted and Moland coastline

3 Results evaluation

An index of performance was developed in order to identify the best performing coastline extraction algorithm. This quantitative index evaluates the success of the segmentation methodology in delineating coastline with respect to an existing reference coastline layer, coming from available geographic data sets. The performance index (PI) is obtained by computing the total area of discrepancies between reference and automatically extracted coastline or water boundaries. Referring to figure 6 the areas of regions, in red and green, bounded by the reference and computed coastlines, were accumulated. The red regions are a set of pixels where the computed coastline overestimate the reference coastline while green area pixels refers to opposite case.

The PI is defined as in equation 4:

$$\mathrm{PI} = 1 - (\sum_{i}^{n} A_i/\mathrm{Npix}) \tag{4}$$

where A_i is the generic area of discrepancies and Npix correspond to the total number of pixel contained in a buffer computed using a fixed distance from the reference coastline. The performance index is evaluated in a test area with complex coastline and water bodies located on the west coast of Norther Ireland (NIE). The reference coastline for this area is a layer from MOLAND (Monitoring Land Use / Cover Dynamics), a research project carried out at the IES - JRC. The Moland coastline for NIE was extracted by a manually digitizing high resolution (5 m), IRS satellite images. Another data set, representing the official coastline layer for the European Commission, stored in a GISCO database was used for PI computation. GISCO is the Geographic Information System for the European Commission, containing spatial layer on hydrography, altimetry, infrastructure data and administrative entities. Table 2 displays the results of the performance of different segmentation algorithm computed using the Moland coastline, the last row of the table show the PI between GISCO and Moland coastline.

Analyzing the PI computation it appears that the SRG algorithm on band 5 with seed regions extracted from the same band delineate land/sea boundaries with good match with respect to the Moland reference Coastline. The performance index PI represents just an indicator to evaluate the performance of different segmentation algorithms, but it cannot be

Table 2: Coastline Performance Index

Segmentation Method	Seeds or Marker Bands	Segmentation Bands	PI on Moland
SRG	DS band 5	band 5	97.5
SRG CORE	DS band 5	band 5	97.34
SRG GRAD	DS band 5	band 5	96.31
SRG	DS band 5	band 5-3-7	96.76
SRG	DS NDWI band 3-5	band 5	96.57
WS	DS band 5	band 5	97.37
GISCO DB	/	/	96.9

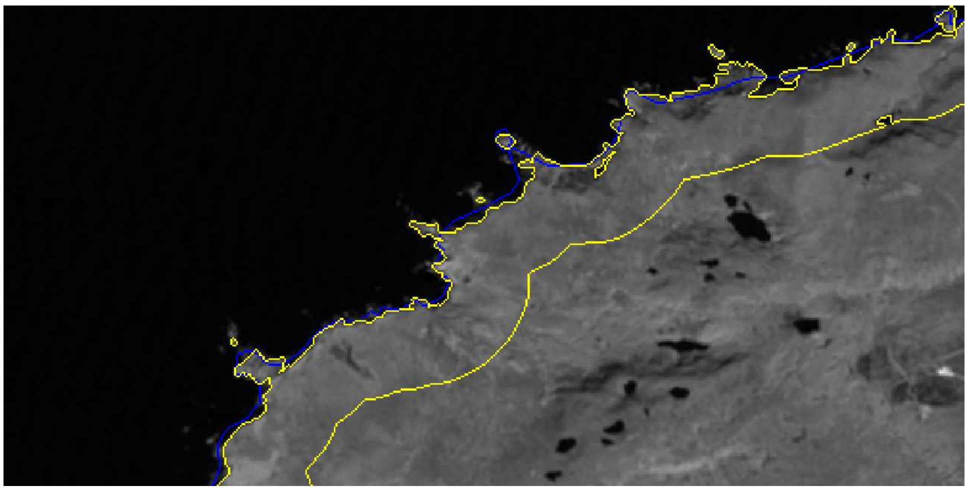

Figure 7: SRG (yellow) from Landsat 7 ETM+ band and GISCO (blue) coastlines

considered as an absolute indicator for the coastline extraction accuracy. In fact it refers to a manually digitized reference coastline that can be subject to human error. In order to evaluate correctly the absolute accuracy of extracted coastline reference land/sea border points from ground surveys (such as GPS observation with simultaneous Landsat 7 ETM+ observation) [Ryu et al., 2002] would need to be available.

Some comparison between the automatically extracted coastline and two available data sets are displayed in figures 7, 8 and 9. From visual analysis of the above maps, it appears that the coastline delineated using morphological operators has a very good fit with the actual coast detected from the Landsat Satellite images.

4 Conclusion

The results of this work demonstrate that region growing and morphological segmentation can be applied to Landsat 7 ETM+ data in order to delineate and map coastline for the entire pan-European Continent. The methodology developed is completely automatic and produces vector files of the coastline which can be analyzed and mapped using GIS tools for European Commission needs. The evaluation of the results through a computation of a performance index demonstrates that the coastline extracted automatically is better that available data sets, such as GISCO coastline.

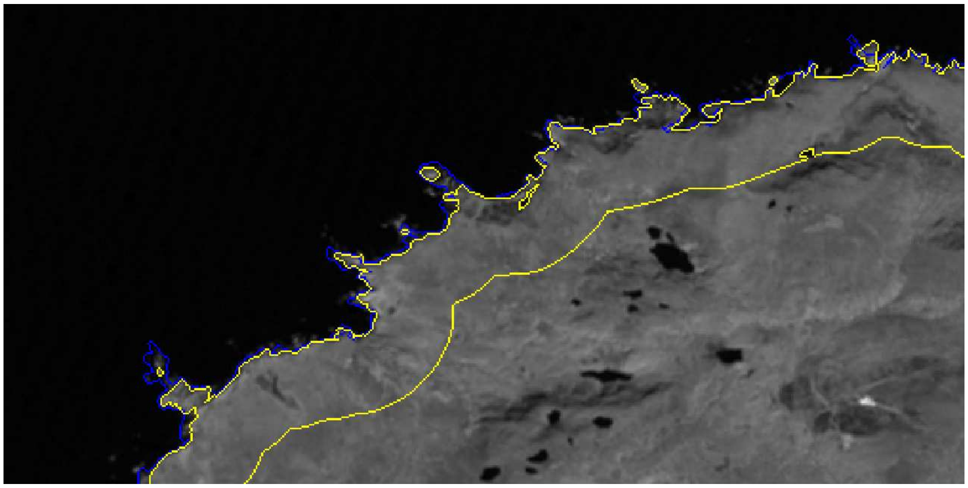

Figure 8: SRG (yellow) from Landsat 7 ETM+ band and Moland (blue) coastlines

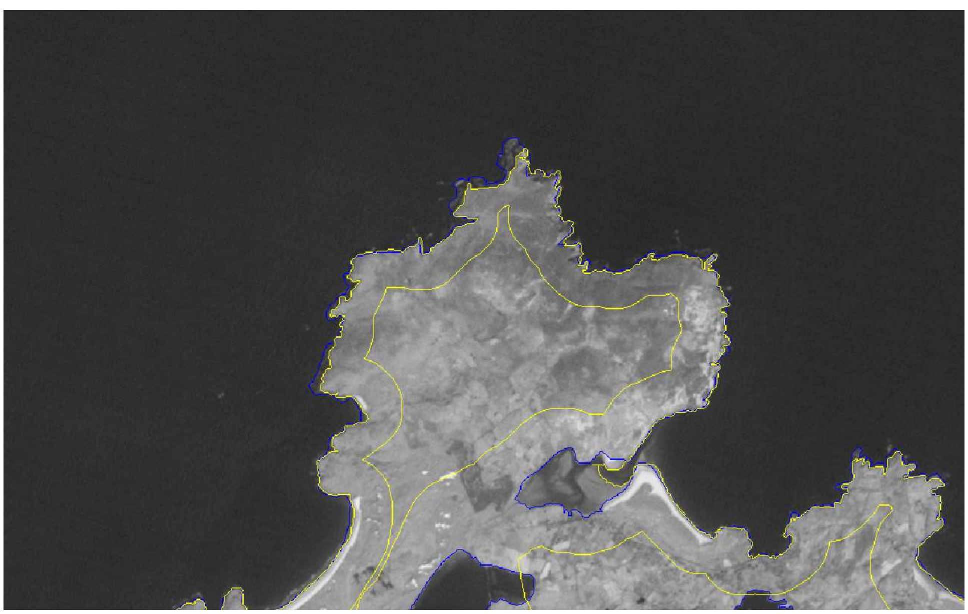

Figure 9: SRG (yellow) from Landsat 7 ETM+ Pan and Moland (blue) coastlines

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