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# HySpex News

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Dear Reader,

Last summer, a major oil spill accident occurred in Norway when MV "Full City" grounded outside Langesund, in a region consisting of several protected areas and popular leisure areas.

30 vessels and 500 people (mainly volunteers) took part in the extensive work associated with minimizing the pollution. The total cost of this operation is estimated to 234 MNok (30 MEuro).

Shortly after the accident, Terratec AS flew an aircraft equipped with NEO's hyperspectral cameras over the Langesund area and recorded very interesting hyperspectral images in the vicinity of the stranded vessel.

In this issue of the HySpex News we would like to present some examples of oil spill detection with basis is these images recorded last summer.

It should be noted that the algorithms that have been employed are standard functions available in commercial software for analysis of hyperspectral images.

We hope this information will be of some interest.

## Hyperspectral Imaging for Oil Spill Detection

### *Background*

From the website of The Norwegian Coastal Administration – NCA:

– *The bulk cargo carrier "Full City" grounded July 31st at 00:23 local time close to the town of Langesund in Telemark, Norway.*

– *MV "Full City" had an estimated 1000 tons of heavy bunker oil (IF 180) and approximately 120 tons of marine diesel oil on board and was in ballast condition when grounding.*

*A considerable amount of oil has spilled from the vessel, and pollution has been observed in the area from Stavern to Grimstad.*

6 days after the grounding of the "Full City", Terratec AS (www.terratec.no) flew one of their Piper PA 31, equipped with HySpex cameras, over the oil polluted area (see Figure 2).

Image acquisition was done from 5000 feet at 135 knots with the VNIR-1600:

- Wavelength range: 0.4 to 1.0 µm
- 160 bands
- 3.6 nm resolution
- 450 m swath
- Pixel size: 0.27 m x 0.54 m (across and along track respectively)


*Figure 1. Full City on ground outside Langesund (Photo: Martin Zeiffert/Kystverket)*

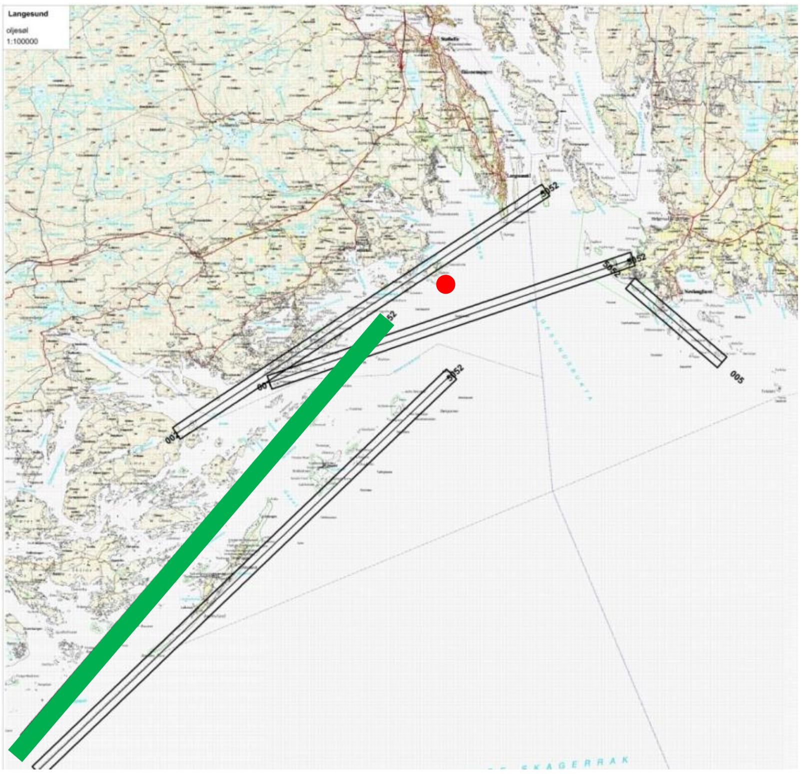


*Figure 2. Terratec' flight plan with the five lines flown in the vicinity of the "Full City". The red circle indicates the location of the vessel. Data acquired along line 3, the green line, is used in this presentation.*

The image on Figure 3, to the left, is an RGB image generated from the hyperspectral data from Langesund. This kind of images is what normally would be obtained from traditional cameras. Here, oil slick on the seawater is slightly visible.

The graphs on Figure 3, to the right, show the at-sensor radiance spectrum of seawater and oil as recorded by the VNIR-1600. The red arrows indicate the locations of the pixels where these "samples" were taken. As can be seen, there are only minute differences between the two spectra.

Images captured during airborne mapping are usually converted to reflectance, thereby removing the effects of the sun spectrum, time-of-day, flying altitude etc. and more clearly render the material properties in the physical scene. A software package, like the ATCOR4, does this conversion. For operational use, it saves valuable processing time if the step of conversion to reflectance can be skipped. Therefore, it was decided to perform the following image analysis with basis in the radiance image, thereby further proving the robustness of the employed algorithms.

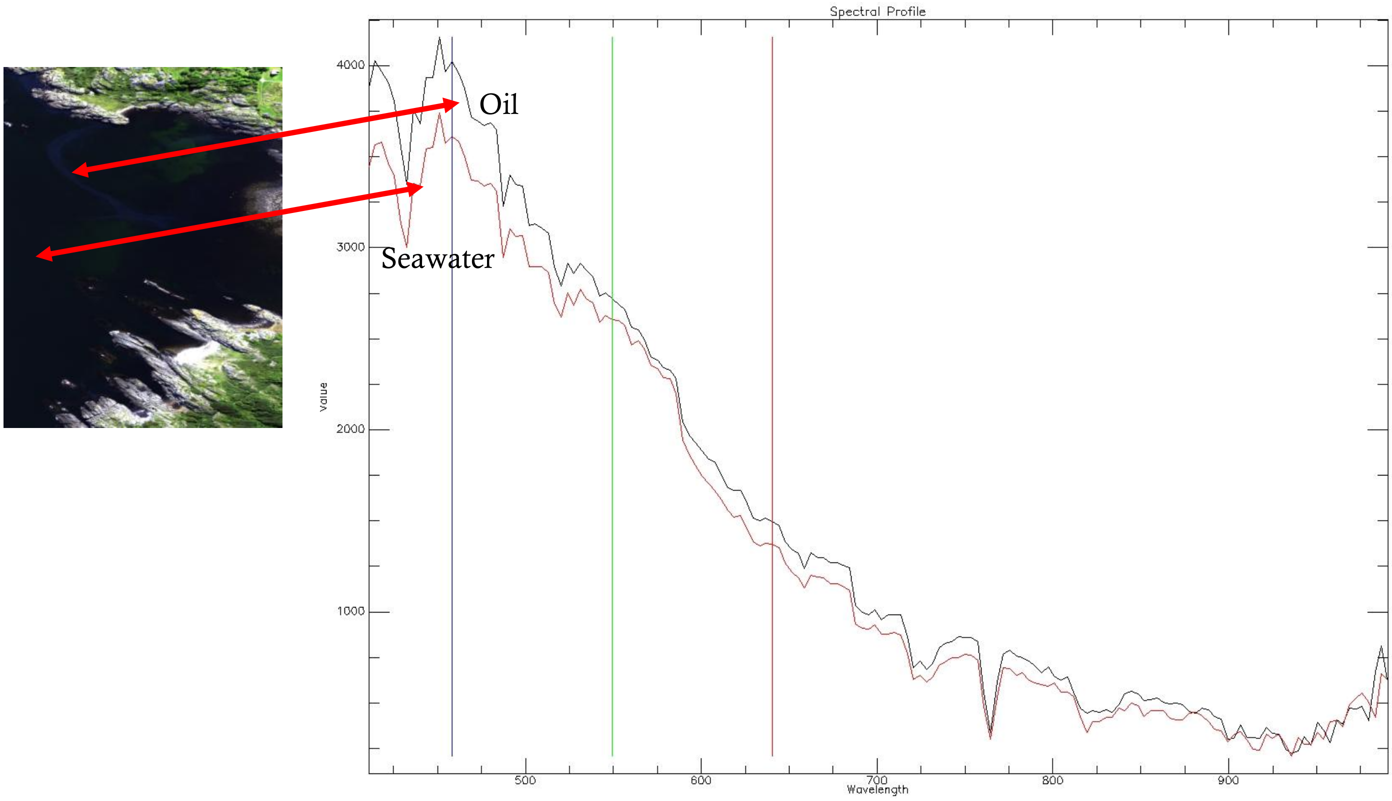


*Figure 3. At-sensor pixel radiance spectra (a.u.) retrieved from the hyperspectral image. In addition to the reflectance of the seawater and oil, these spectra include the contribution from the sun spectrum as well as various atmospheric effects. The results presented in the following are based on data in this format.*

## *Supervised versus unsupervised classification*

It is the objective of this paper to show some preliminary results using standard image analysis algorithms for classification of oil on seawater. An unsupervised classification method and a supervised classification method have been employed.

In unsupervised classification, each pixel is compared to the defined discrete cluster to see which one is closest. A map of all pixels in the image, classified as to which cluster they belong, is produced (in colours representing each cluster). The user has to interpret what the colour patterns may mean in terms of classes, etc. that are actually present in the real world scene; this requires some knowledge of the scene's feature/class/material content from general experience or personal familiarity with the area imaged.

In a supervised classification the interpreter knows in advance what classes, etc. are present and their locations. One class may be found in one or perhaps many locations within the scene. Training sites for the classification algorithm are defined by locating the different classes on the image. All pixels in the image lying outside training sites are then compared with the class discriminants derived from the training sites, with each being assigned to the class it is closest to - this makes a map of established classes (with a few pixels usually remaining unknown) which can be reasonably accurate (but some classes present may not have been set up; or some pixels are misclassified.

## *Principal Component Analysis (PCA)*

PCA plays an important role in the processing of remote sensing images. Even though its theoretical limitations for hyperspectral data analysis have been pointed out, in a practical situation the results obtained using PCA are still competitive for the purpose of classification. The advantages of PCA are its low complexity and the absence of parameters. However, PCA only considers the second-order statistic, which can limit the effectiveness of the method.

As a first assessment of the feasibility of oil/water separation, a Principal Component Analysis (PCA) was run on a section of a hyperspectral image. Figure 4 shows a colour image generated with basis in three bands from the PCA. These bands were the ones giving the highest contrast between oil and water. As can be seen, the oil floating on the seawater is clearly separated from the varying background. The basis for having success with classification algorithms should consequently be present.


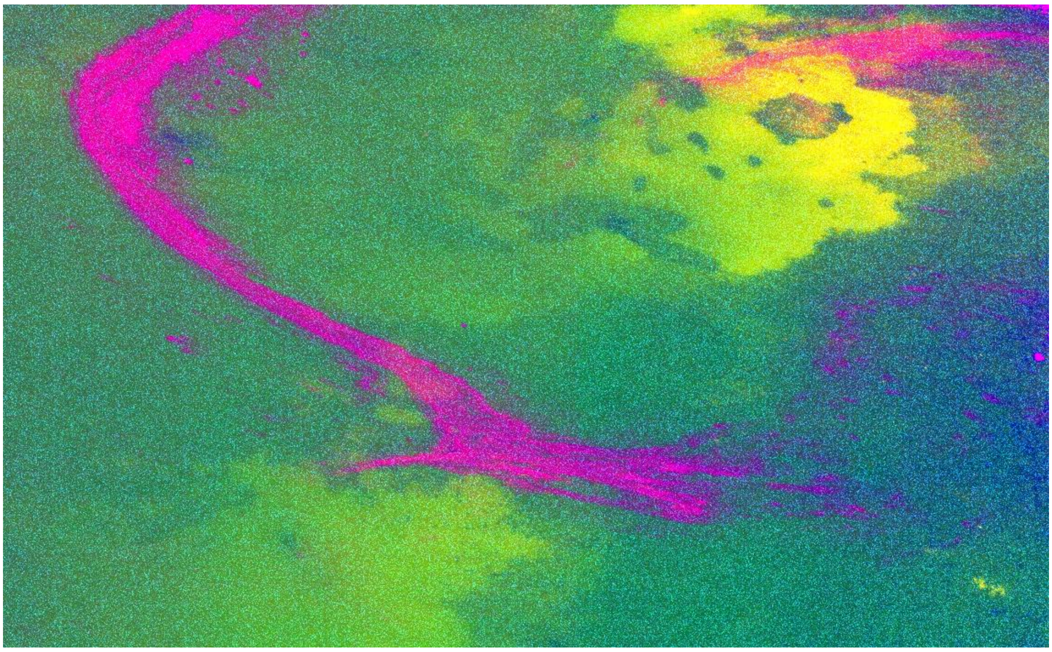

*Figure 4. Left: RGB-image showing an overview of a polluted area. Right: image generated from three eigenvectors from the PCA (Pink = oil on seawater, Yellow = sand on sea floor, Green = Seawater).*

## *K-means*

The K-means algorithm is an unsupervised classification method, which automatically distributes pixels onto a specified number of evenly distributed classes in data space. Roughly, the algorithm works as follows:

1. The number of initial centroids k (classes) is defined.

2. For each pixel in the image, the distance to each of the k centroids is calculated. The pixel is assigned to the centroid associated with the smallest distance (here, distance means the Euclidian difference between the spectral signatures, the reflectance at each band).

3. When all pixels are assigned to one of the k centroids, i.e. the pixels are grouped in k groups. The centroid of each group is recalculated and the algorithm is repeated from step 1 with these new centroids. The algorithm is repeated until the process is stable of has reached a minimum threshold.

4. Each pixel is given the colour of the centroid (classes) it has been assigned to and the image is reconstructed using these colours.

Figure 5 shows the results from the K-means, where the number of classes was set to 20 and the algorithm was run once only.

The K-means process clearly separated oil floating on the seawater, both freely floating and along the shore.

Note that the PCA revealed an area comprising sand on the sea floor (yellow areas in Figure 4). The K-means, with the settings described above, failed to render the correct oil distribution in this area. This may be improved by changing the processing parameters.


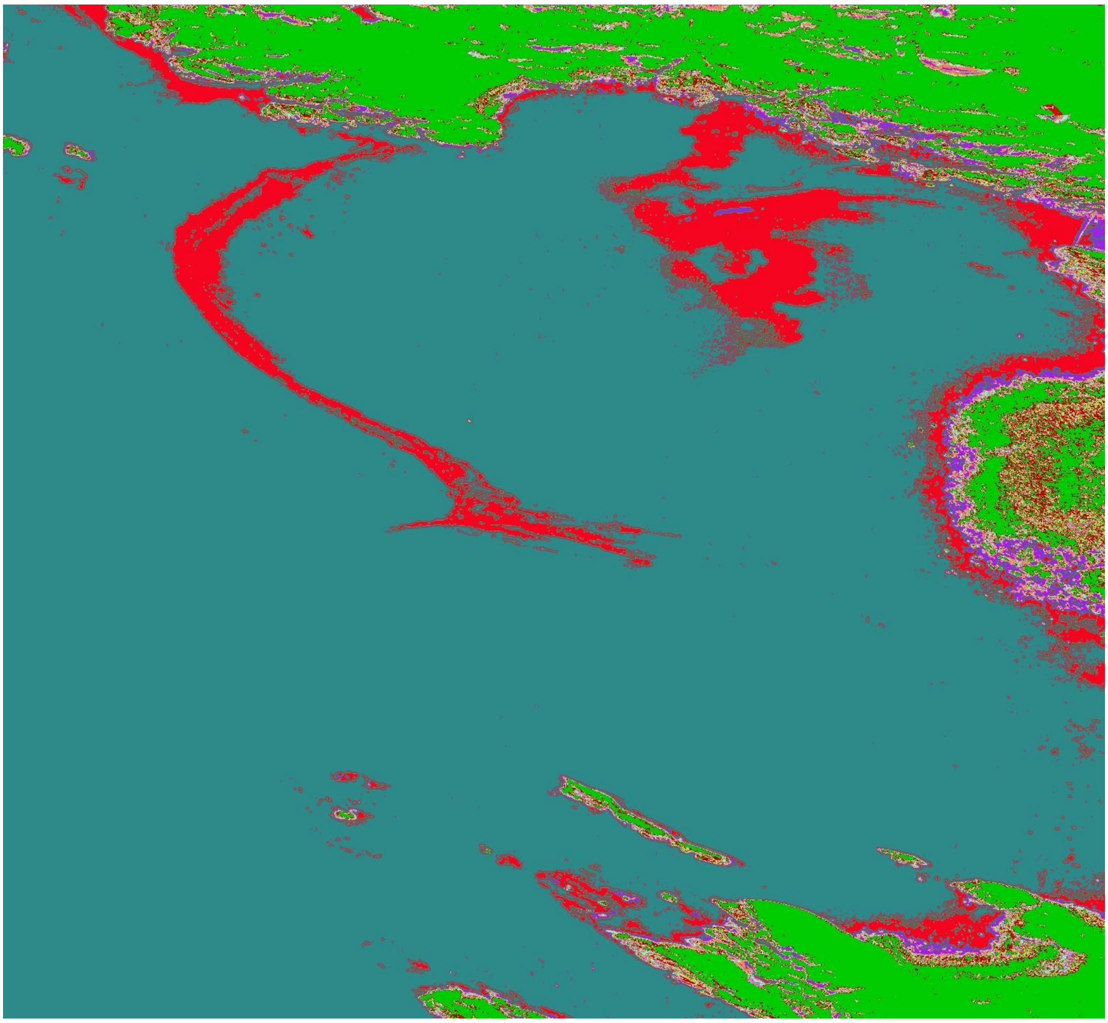

***Figure 5*** *Left: RGB-image. Right: image generated by the K-means algorithm (Turquoise = Clean seawater, Red =oil, Green = vegetation on land).*

Figure 6 shows the result of the K-means algorithm employed on a larger image, 20 classes and the algorithm run once. Oil on seawater is classified, both in open sea (upper right image) and close to shore (lower right image).

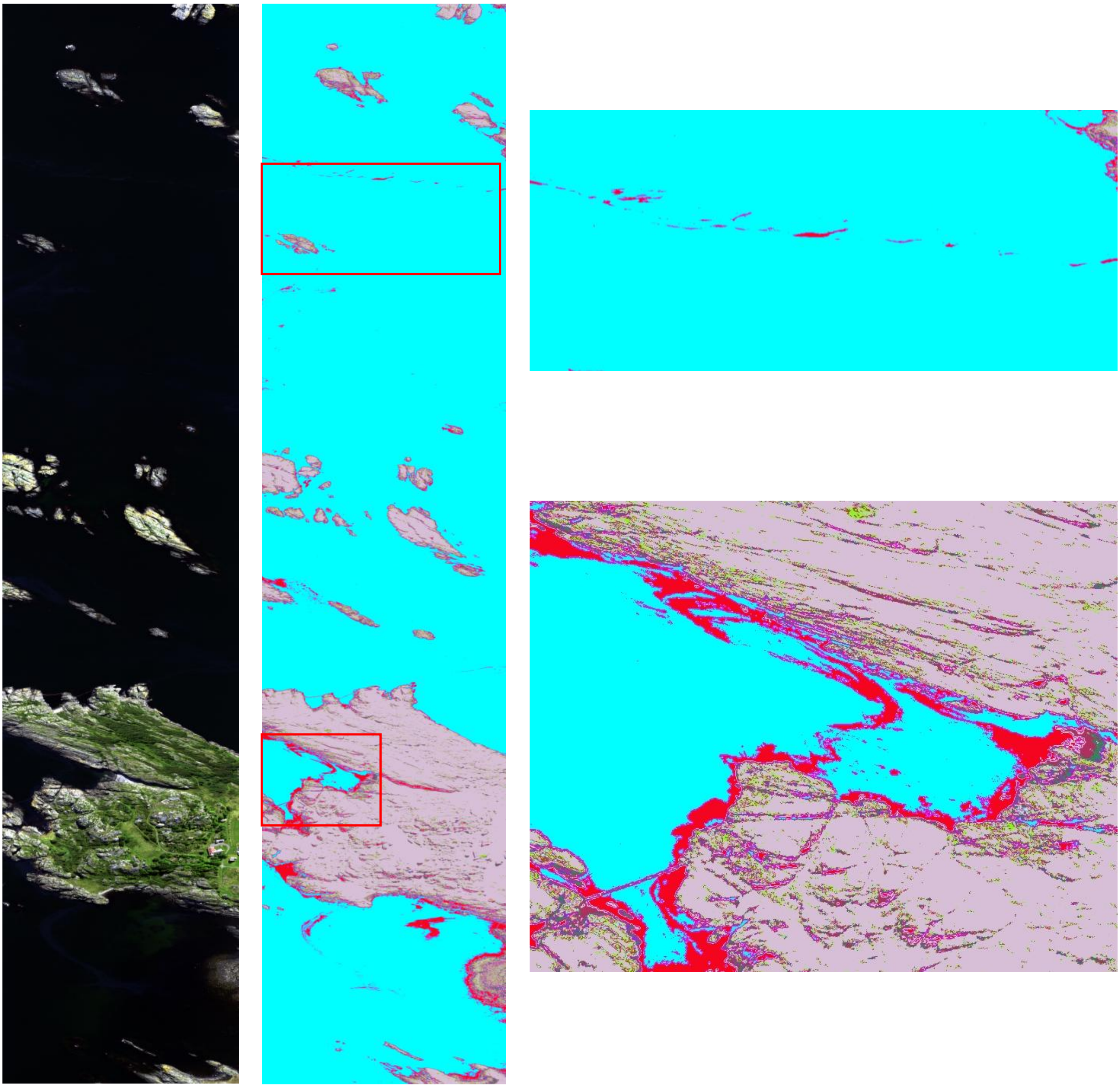

*Figure 6. Classification of oil on a larger image. Left: RGB-image. Right: image generated by the K-means algorithm ( Red =oil).*

## The Minimum Distance Classification

The minimum distance technique is a supervised method, which calculates the mean vectors for each endmember (class) and calculates the Euclidian distance from each unknown pixel to the mean vector for each class. All pixels are classified to the nearest class unless a threshold is specified.

Figure 7 shows the result from the minimum distance classification. Here, 8 classes were defined by "manual sampling" of the hyperspectral image.

By proper definition of the endmembers, the minimum distance method manages to separate the floating oil from the sand on the sea floor.

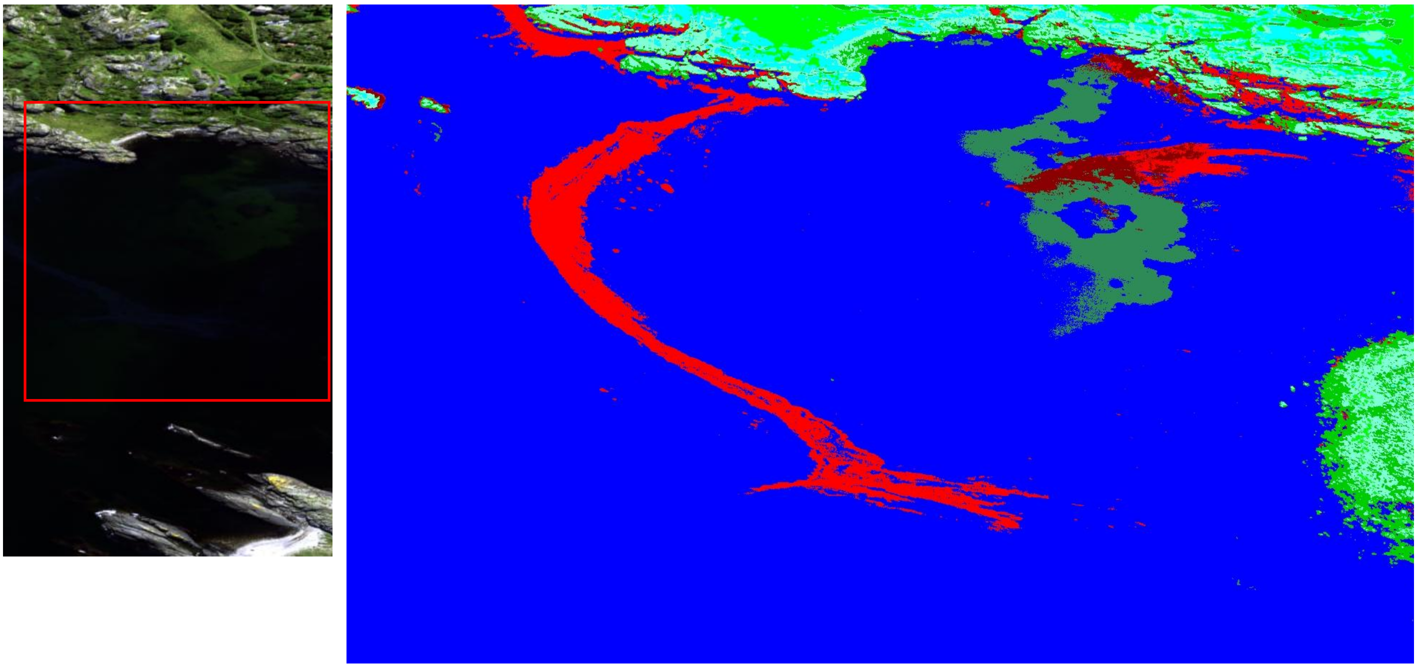

**Figure 7.** *Left: RGB-image. Right: image generated by the minimum distance algorithm ( Red =oil on sea water, Blue = Seawater Olive green = Sand on seabed).*

## Conclusion

The preliminary analysis shows convincing results, with respect to discrimination of oil on seawater, by the use of standard tools for hyperspectral image analysis:

- K-means
- Principle component analysis
- Minimum distance algorithm

With basis in the hyperspectral images acquired with the VNIR-1600 from the airborne platform, floating oil with an extent of a few pixels (< 1 $m^2$) is separated from the seawater.

The processing time is adequate for use in real operational scenarios, especially if NEO's real-time processing system is employed (see HySpex News January 2010).

More in-depth analysis and other algorithms may improve the results.

Sub-sets of data used for this analysis can be made available upon request.