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Evaluation of Underwater Hyperspectral Imagery (UHI) for MAREANO

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NO-7491 TRONDHEIM
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Evaluation of Underwater Hyperspectral Imagery (UHI) for MAREANO

Authors:
Margaret F.J. Dolan, Terje Thorsnes, Pål Buhl-Mortensen, Lilja Rún Bjarnadóttir, Stefan Ekehaug, Lars Martin Sandvik Aas, Jørgen Tegdan, Martin Ludvigsen

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Summary:

As part of a method development initiative in the MAREANO seabed mapping programme (www.mareano.no) a pilot survey using Underwater Hyperspectral Imagery (UHI) was undertaken in Trondheimsfjorden during December 2014. Ecotone AS provided all technology and services related to the acquisition and processing of UHI data, while the Applied Underwater Robotics Lab (AUR-Lab), part of the Norwegian University of Science and Technology (NTNU), provided the Remotely Operated Vehicle (ROV) and associated technical support for UHI mapping which was conducted from the NTNU research vessel 'Gunnerus'. MAREANO scientists from the Geological Survey of Norway (NGU) and the Institute of Marine Research (IMR) participated in the cruise with a view to evaluating the potential of UHI for geological and biological mapping respectively. Processing of data and presentation of results was undertaken by Ecotone AS during 2015 and provide the basis for evaluation by MAREANO. The fieldwork, results and evaluation of relevance of UHI technology for MAREANO are summarised in this report.

The findings of this pilot study indicate that there is considerable potential in the UHI methods for both biological and geological mapping. At the time of the 2014 pilot survey in Trondheimsfjorden the UHI technology was not sufficiently mature to deliver data and results that could give clear added value to the regional scale mapping performed by MAREANO. Nevertheless, we acknowledge that development by Ecotone, coupled with experience from other projects since 2014, mean that UHI hardware and software capabilities are now [October 2016] considerably more well developed than when the pilot study was undertaken. These improved capabilities have not been directly assessed as part of this study but are summarised in the report for information.

If the UHI could be installed as an extra sensor on the underwater imaging platform used for MAREANO surveys then testing and development of spectral libraries for offshore areas could potentially be initiated as a collaborative research venture by Ecotone and MAREANO. Either through such a collaborative venture, or other relevant projects, it will be important for Ecotone to demonstrate readiness of hardware, software and MAREANO-relevant data products before investment in, or standard use of, UHI technology by MAREANO can be considered.

Keywords: Marine geology	MAREANO	Seabed mapping
Marine biology	Hyperspectral Imaging	Underwater survey
ROV	Marine technology	Trondheimsfjord

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1. INTRODUCTION

The MAREANO seabed mapping programme has been in operation since 2005 and in recent years has made a dedicated effort to explore and evaluate new technologies for seabed mapping within an ongoing aim of keeping MAREANO methods up to date. One such emerging technology is Underwater Hyperspectral Imaging (UHI), an optical remote sensing method adapted from terrestrial usage to underwater application by scientists at the Norwegian University of Science and Technology (NTNU) and now developed and operated commercially by Ecotone AS, Trondheim.

Following presentations and demonstrations of UHI by NTNU and Ecotone, MAREANO identified UHI as a potentially useful tool for seabed mapping. As part of the MAREANO method development initiative a proposal was approved in 2014 to test and evaluate the potential for use of Underwater Hyperspectral Imagery (UHI) for use in MAREANO mapping activities. As a result MAREANO formed an agreement with Ecotone AS to conduct a pilot survey in Trondheimsfjorden in December 2014. Ecotone provided all technology and services related to the acquisition and processing of UHI data, while NTNU’s Applied Underwater Robotics Laboratory (AUR-Lab) provided the Remotely Operated Vehicle (ROV) and associated technical support for UHI mapping which was conducted from the NTNU research vessel ‘R.V. Gunnerus’. MAREANO scientists from The Geological Survey of Norway (NGU) and the Institute of Marine Research (IMR) participated in the cruise with a view to evaluating the potential of UHI for geological and biological mapping respectively. Processing of data and presentation of results was undertaken by Ecotone AS during 2015 and provide the basis for evaluation by MAREANO. The fieldwork, results and evaluation of relevance of UHI technology for MAREANO are summarised in this report.

1.1 UHI background

Remote optical sensors measure the reflectance (i.e. brightness and colour) of a given object. Sensors vary in the amount of spectral (colour) information they can capture and hence in their ability to discriminate between different objects. Three-channel sensors such as the red-green-blue (RGB) wavebands detected by the human eye give much more information than monochrome sensors. Multispectral sensors, like the eye of a mantis shrimp, can detect up to 20 specific wavebands and are therefore even better at discriminating between coloured objects (Figure 1). Sensors capable of detecting more than 20 wavebands are classed as ‘hyperspectral’. In remote sensing terms, the colour spectrum measured by hyperspectral cameras can be regarded as continuous. The high colour resolution allows the hyperspectral camera to detect and discriminate between colours and objects not visible to the human eye, or standard RGB camera. Specific chemical signatures corresponding to internal electron transitions in materials can also be observed by hyperspectral sensors and classified as so called ‘optical fingerprints’.

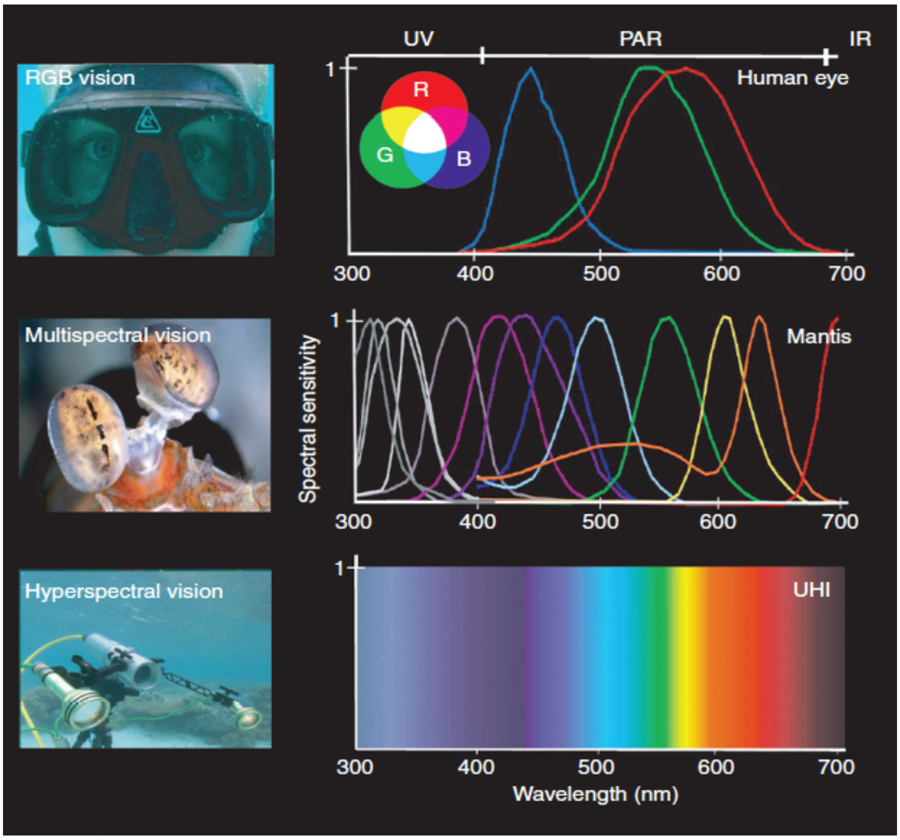


Figure 1. A comparison of colour bands used in RGB vision (humans), multispectral vision (mantis shrimp) and hyperspectral vision. The graphs are visualizations of the bands in the visible part of the electromagnetic spectrum, showcasing the hyperspectral imager’s high spectral resoluion (1nm) (Johnsen et al., 2013)

Hyperspectral imaging from airborne platforms is a relatively well established technology with a variety of applications including vegetation and geological mapping in coastal and terrestrial environments (see Aarrestad, 2014, Volent et al, 2007, Chang et al. 2004). However, use of hyperspectral imaging under the water presents several challenges, mainly related to the natural optical properties of the water column. Water has a relatively narrow transparent spectral band that limits the use of underwater hyperspectral imaging (UHI) to the visible range. It seems that, with the exception of specially adapted UHI developed and used by NTNU/Ecotone (Johnsen et al. 2013) and a spectrometer-based system developed at the University of Sydney (Bongiorno, 2015), hyperspectral imaging has thus far been limited to clear, shallow waters. Here, penetration of sunlight to the seabed is sufficient for passive operation of hyperspectral imagers. For underwater use in deeper and more turbid waters, the hyperspectral imager must be used in active remote sensing mode i.e. with an artificial broadband light source. This allows the UHI to get closer to the seabed and objects of interest (OOI) and gain better spatial, spectral and radiometric (bit per pixel) resolution of the optical measurements. Due to the artificial light source UHI also opens up the option of revisiting a site to detect changes over time under the same optical conditions. This means UHI has the potential to provide a greater temporal resolution than passive hyperspectral imaging which is affected by changes in natural lighting conditions (e.g. cloud cover, etc.). Whilst the use of an artificial light source opens up benefits, it also imposes practical limitations because the survey altitude is limited by the optical power of these light sources and also by variations in the water quality (Lee et al. 1999; Johnsen et al. 2013).

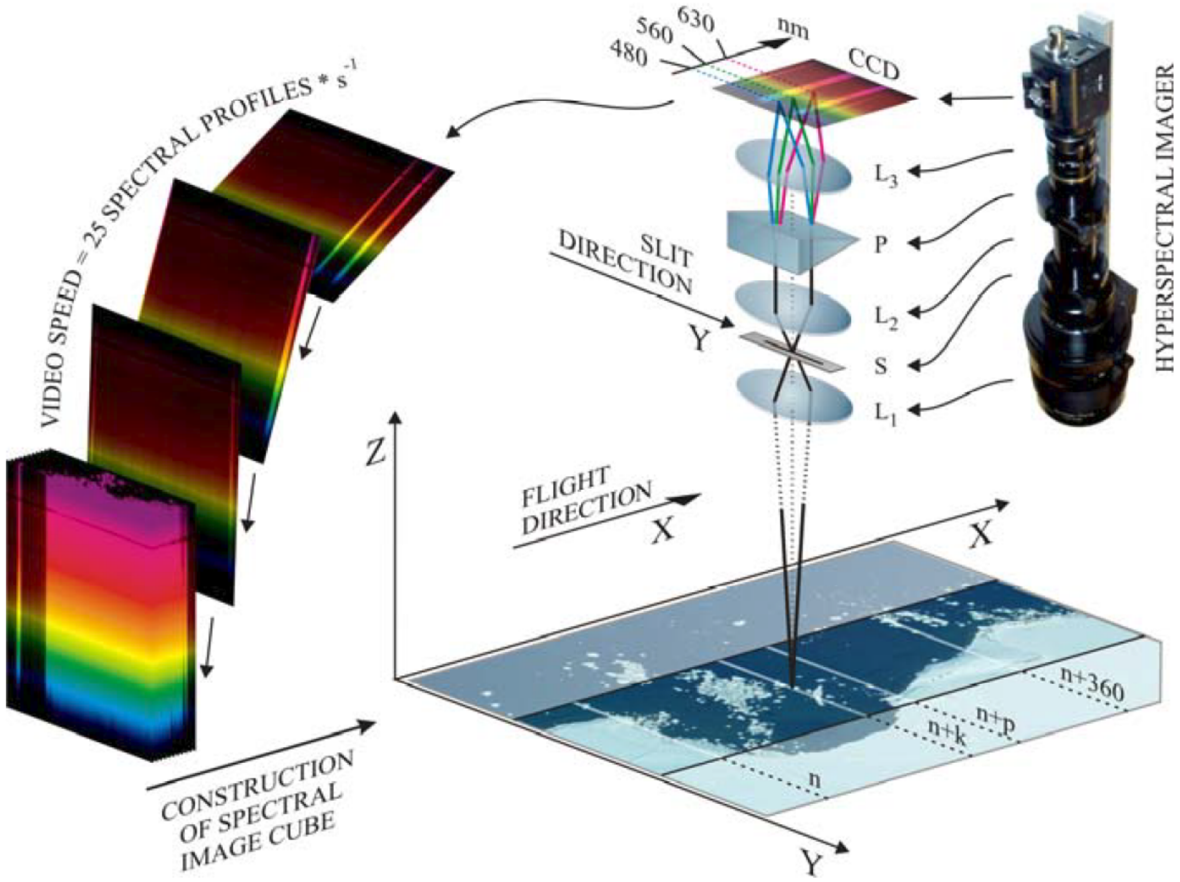


Figure 2. Model illustrating the hyperspectral imager, the "push broom" technique and the spectral image cube. L1 = front lens, S = entrance slit, L2 = collector lens, P = prism, L3 = camera lens and CCD = imaging detector (Charged Coupled Device), n = amount of pixels in X-direction (from Volent et al., 2007)

The UHI system used by Ecotone AS in this study consists of the imager in an underwater housing and external broadband illumination. As a push-broom line scanner (Figure 2), it faces the seafloor and records frames perpendicular to the direction of platform movement. When deployed on a tethered underwater platform fiber-optics connect the UHI to a topside computer which stores all data and allows a live view and control of the UHI. Hyperspectral data are typically recorded in parallel with standard video surveys.

All UHI measurements require corrections for the apparent and inherent optical properties of the water column since substances in the water absorb and scatter light, affecting the true reflectance of the target OOI. Corrections must also be made for the light intensity and spectral characteristics of the light source as well as for any ambient light present at the operating depth. Further description of the technical details of these corrections are beyond the scope of this report, but readers are referred to Johnsen et al. (2013) for more information.

1.2 Associated platforms and sensors for UHI

The UHI system can be mounted on a variety of underwater survey platforms (Figure 3) making it possible to map large areas with a more automated approach (Johnsen et al. 2013). Due to the requirement for highly accurate geo-localisation, the survey platform must be equipped with a dynamic underwater positioning system including motion sensors. The platform must also be equipped with good light sources. Sensors for measuring water column optical properties (Chlorophyll a, coloured dissolved organic matter, and total suspended matter) are also required for optical processing.

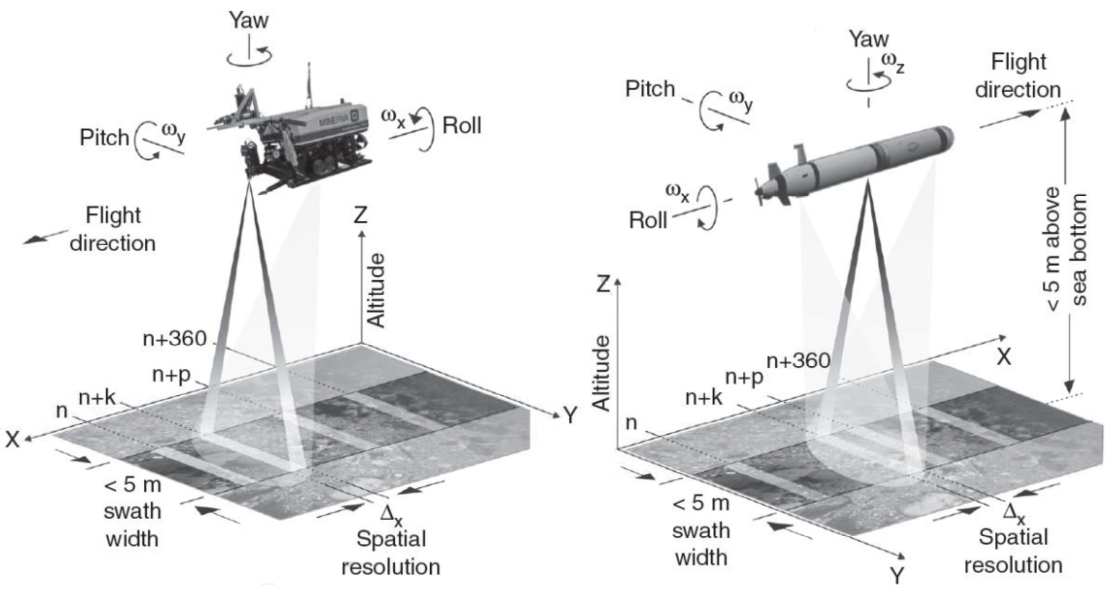


Figure 3. Illustration showing UHI deployed on (a) ROV (Sperre Subfighter 7500) or (b) on AUV (Hydroid Remus 600, Kongsberg Maritime) equipped with artificial light sources to illuminate OOI on seafloor. From Johnsen et al. (2013).

Remotely operated vehicles (ROV) are the most commonly used platform to date and provide a relatively good, stable platform for UHI data acquisition with both power and communication coming via a tether (umbilical fibre optic cable). This direct contact with the ROV means that UHI data can be viewed by the top-side operator in real time (typically alongside standard video) and this is helpful for rapid diagnosis of any problems. The direct power supply to the ROV also means that power payload to lights and external sensors is not limited. Since ROVs are tethered to the surface vessel and manually operated, however, they can be prone to unwanted motion (pitch, roll, yaw) and deviations from the planned survey route, depending on sea conditions and pilot expertise. These platform motions can disturb the recorded images and have to be measured and corrected for in post processing. In addition, thruster motors on the ROV can disturb unconsolidated sediments when mapping close to the seabed, increasing water turbidity which reduces image quality.

Some ROVs have the option of autonomous operation (e.g. Ludvigsen et al., 2014). This means the ROV follows a pre-programmed path at a given altitude and thereby operates much more like an autonomous underwater vehicle (AUV) using dynamic positioning. Although there is still an option for pilot intervention, the ROV operates for the most part without human intervention and this can help minimise deviations from the planned path and motion effects. Cleaner UHI data during acquisition means faster and more effective processing, so this is the preferred mode of operation for UHI surveys.

Another option for minimising motion effects is to use an AUV as the survey platform. AUVs have integrated controllers for vehicle heading, altitude, velocity and a cross-track error that allows for accurate survey lines to be followed. Use of an AUV frees the survey platform from a tether to the ship and makes it more practical to survey large areas, along pre-defined survey routes with precise manoeuvring. This can improve acquired data quality, therefore decreasing the required post-processing and ultimate quality of the processed data. Whilst AUVs may offer several benefits that overcome difficulties associated with ROVs, they also offer some challenges, including limited power supply and a lack of online viewing of data during acquisition. The choice of the best underwater platform for any given survey is therefore a matter of compromise between the benefits offered by ROV or AUV.

1.3 NTNU and Ecotone

A thorough review of UHI technology and applications is given by Johnsen et al, (2013), including several examples from the laboratory and field development and testing at NTNU. Pettersen et al. (2013) provide further description of the development of UHI as a bio-optical taxonomic tool including results of field mapping of cold-water corals and other pigmented organisms in Trondheimsfjorden using a prototype UHI on mounted on a sled (Figure 4).

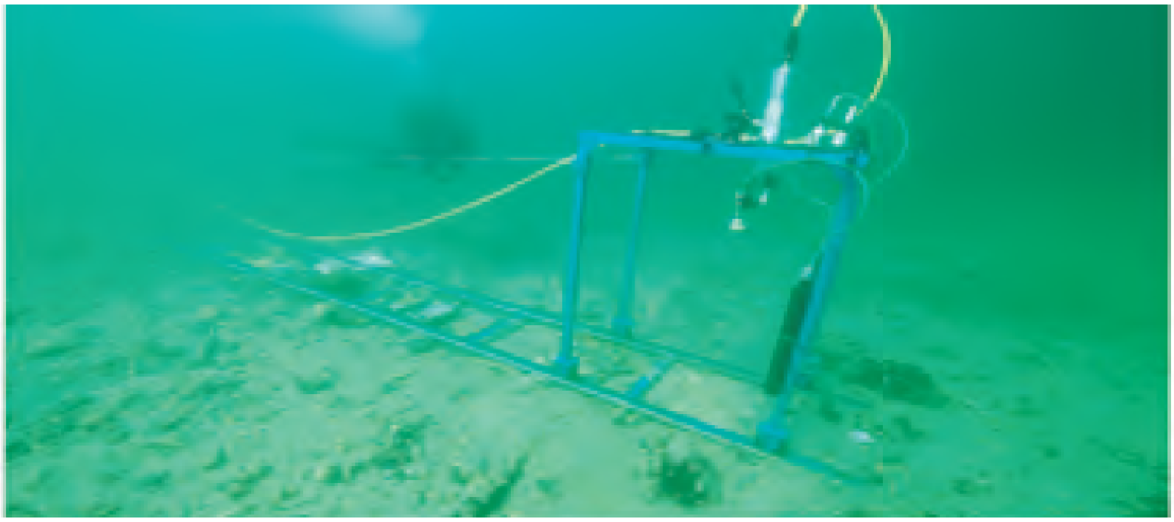


Figure 4. Set up of an UHI prototype seafloor mapping of biogeochemical OOI in April 2010 in Hopavågen, Norway. The prototype UHI was mounted on an underwater sled with artificial light sources. Extract from Johnsen et al. 2013.

Further mapping was conducted with UHI in Trondheimsfjorden including UHI surveys of Tautra ridge in 2012, which is colonised by the cold-water coral *Lophelia pertusa*, and associated fauna (Ludvigsen et al. 2014). Figure 5 shows an RGB image of hyperspectral imagery from this area (acquired at a later date). Note that the information used for analysis and classification of such data does not come from these RGB images but from reflectance spectra of the OOI inherent in each pixel in the fully processed image.

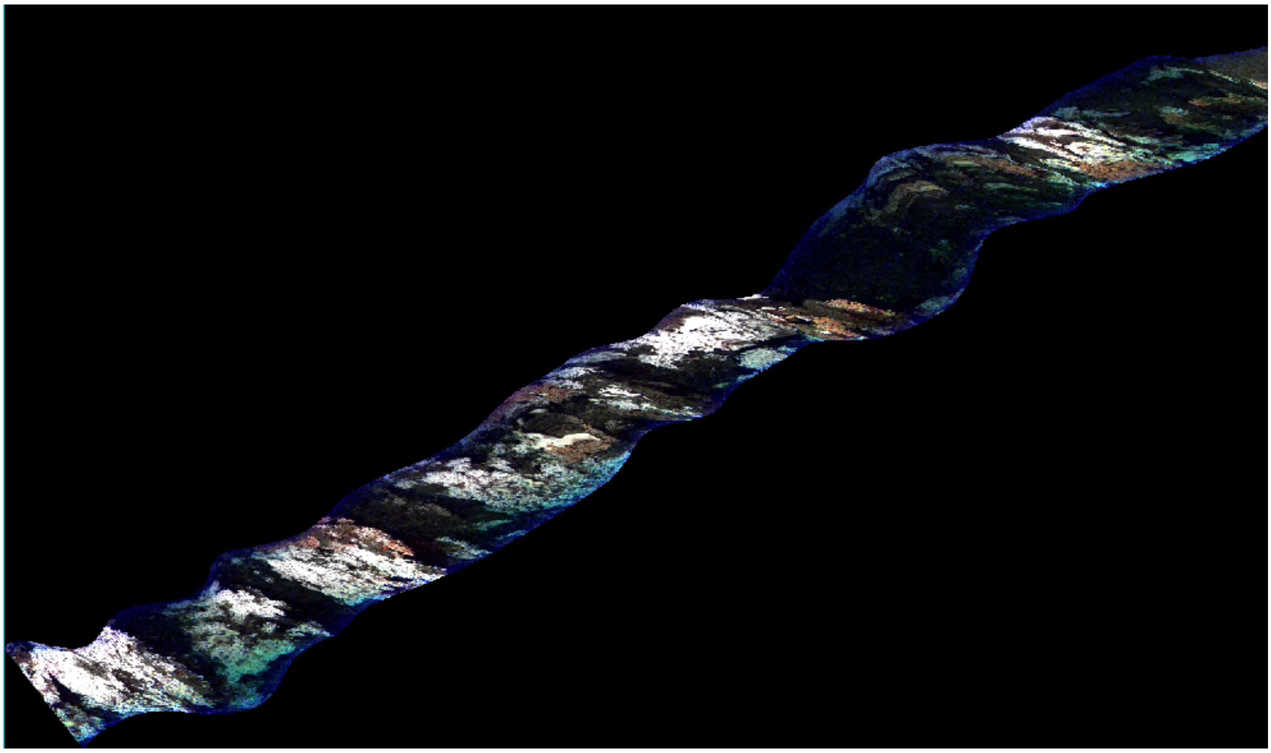


Figure 5. Geocorrected UHI image showing white and orange Lophelia pertusa *on a 20m long section of the Tautra cold-water coral reef.*

Whilst the first applied studies of UHI technology focussed on biological OOIs, investigation of UHI for geological mapping has recently begun with a laboratory-based study for a Master of Science degree by Aarrestad (2014). This thesis provides a good review and background on the use of hyperspectral imaging for geological mapping with special focus on seabed mapping. Laboratory investigations of artificial and natural sediments explored the potential of UHI for determining calcium carbonate content, mineral properties, organic content, and grain size. Results were promising, yet confirmed a need for further studies and development of UHI technology to detect geological properties, particularly in the field. These and other possible geological applications of UHI are indicated in Figure 6.

Ecotone is a spin-off company from NTNU which aims to develop and commercialise the UHI technology originating from NTNU. Ecotone is owned by Statoil Technology Invest, NTNU Technology Transfer, founders and employees. Ecotone has patented the technology for use of hyperspectral imaging under water (Johnsen, 2014) . Ecotone currently has ten employees and one post doctoral position affiliated to the company.

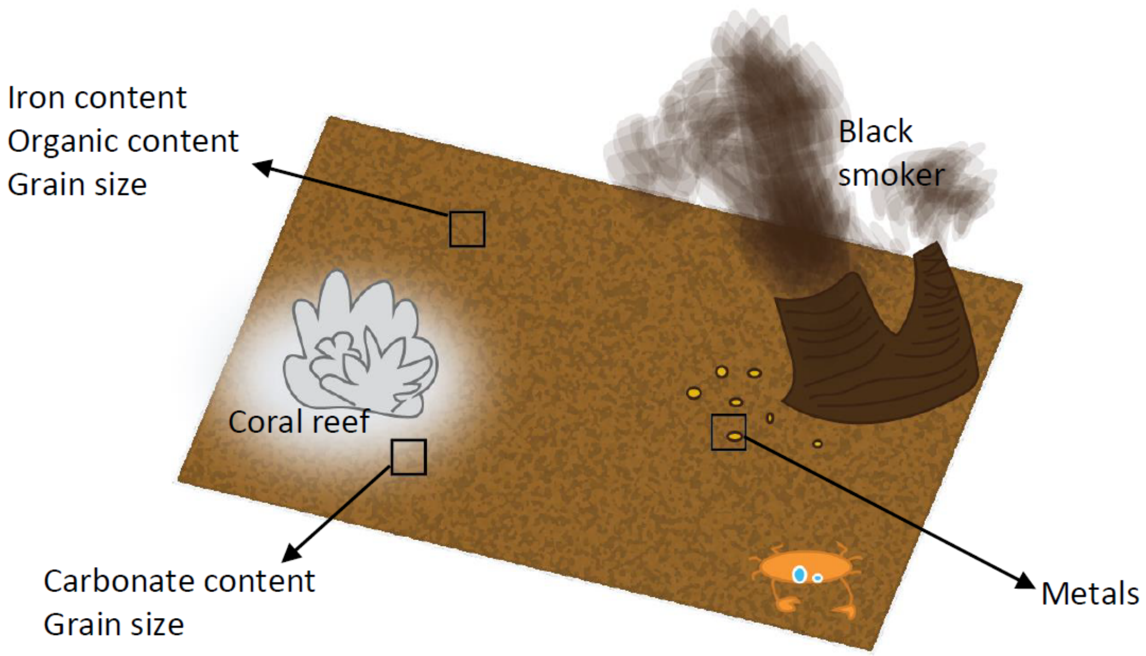


Figure 6. Conceptual illustration of the seabed and possible geological application of UHI. Features are indicative and not drawn to scale. (from Aarrestad, 2014).

Ecotone have demonstrated the potential value of UHI technology through various industry and research projects. The most notable project is a Joint Industry Project (JIP) Petromaks 2: New technology and methods for mapping and monitoring of seabed habitats. This project aims to develop UHI further as a tool for mapping and monitoring of the seabed, as well as evaluating the potential for assessing the health of marine organisms by use of UHI as a remote sensor. The project is sponsored by five partners in the oil industry, as well as the Norwegian Research Council and Norwegian Deepwater Program.

Ecotone maintains close links with NTNU, in particular the AUR-Lab which has expertise in operation and control of underwater robotic systems. Ecotone and NTNU will continue to collaborate on various research and development projects, as there are mutual benefits within many areas through such a collaboration.

Going forward, the company will continue developing the UHI sensor system and data processing software including algorithms for automatic detection and identification of benthic fauna and underwater objects, improving the quality of results and the time it takes to map an area, and also extending the range of survey platforms from ROV to include AUVs and other platforms. There is also interesting potential for using the technology for an increased range of applications, e.g. aquaculture, deep sea mining and subsea infrastructure inspection.

2. PROJECT DESCRIPTION

UHI data acquisition was undertaken in Trondheimsfjordenen from 10-11 December 2014 using an ROV operated from NTNU's research vessel 'R/V Gunnerus'. It was intended that data from this cruise would give MAREANO (NGU, IMR) access to sufficient raw and processed data of suitable quality to be able to evaluate UHI as a potential tool for mapping under the MAREANO programme. Further, MAREANO would offer recommendations to Ecotone and AUR-Lab for future development directions relevant to geological and biological seabed mapping. Ecotone, in conjunction with AUR-Lab, facilitated data acquisition, processed and delivered the data.

Following the cruise Ecotone transferred the following data to MAREANO:

a) Processed RGB images from UHI together with classified data in ArcGIS compatible raster format. Classification targeted the most common biological species and man-made objects of interest. Raw data including spectral information requires specialist and proprietary software – NGU/IMR access to these data was facilitated by Ecotone at their premises in Trondheim.
b) Standard and HD video data in generic digital format (from AUR-Lab).
c) All supporting ROV position and motion sensor data in generic, Geographic Information System (GIS) compatible formats (from AUR-Lab).

The results of the projected are the shared property of MAREANO, Ecotone and AUR-Lab and all parties have contributed to reporting. Any further publication of results will also be done in partnership.

3. FIELDWORK

3.1 Location

The area selected for UHI test surveys is located off Agdenes, close to the mouth of Trondheimsfjorden (Figure 7). The site lies at around 600 m water depth and is the deepest part of Trondheimsfjorden. Currents in this area vary at different depths in the water column, which can present challenges for ROV operation. Currents exceeding 10 cms^{-1} are quite common in the upper part of the water column, while bottom currents are generally weaker (I. Erlingsen, SINTEF, pers. comm). Nevertheless tidally associated currents below 100 m water depth of up to 100 cms^{-1} have been recorded at Agdenes (Bakken et al. 2000) indicating how periodically dynamic the hydrodynamic regime is in this area. During the survey period 10-11 December 2014 the tidal range was approximately 2 m and survey operations were planned to avoid the strongest tidal currents.

In the years following World War II this part of Trondheimsfjorden became a dumping ground for bombs, ammunition crates and associated artefacts. A number of ships have also been sunk here. Over time, these artificial objects have been colonised by benthic organisms, but other effects of the dumped material on the seafloor are not yet known. Previous studies by NGU (Bøe et al. 2000, 2003) had indicated that the area is subjected to erosion and/or non-deposition, associated with the currents mentioned above. This means that any dumped material may be subject to resuspension and lateral spreading.

Recent acoustic, photo and video data acquired by AUR-Lab and the Norwegian Defence Research Establishment (FFI), in partnership with NGU, have re-awoken scientific interest in this area. These overlapping surveys, employing different technologies make the dumping ground a good test area for seabed mapping technology within Trondheimsfjord.

The UHI surveys conducted for this project were designed to provide an opportunity to demonstrate the suitability of the technology for (a) line surveys, as currently used by MAREANO for bio-geo video surveys and, (b) full coverage surveys of a compact area. To provide data comparable with MAREANO’s current standard of 700 m long video surveys, three 500 m line surveys were conducted using UHI from the ROV. In the middle of one of these lines a 20 x 25 metre box was surveyed with full coverage by running a lawnmower-pattern survey (Figure 8). The locations were selected to maximise the variety of seabed sediment types, with dumped objects providing artificial ‘hard’ substrates.

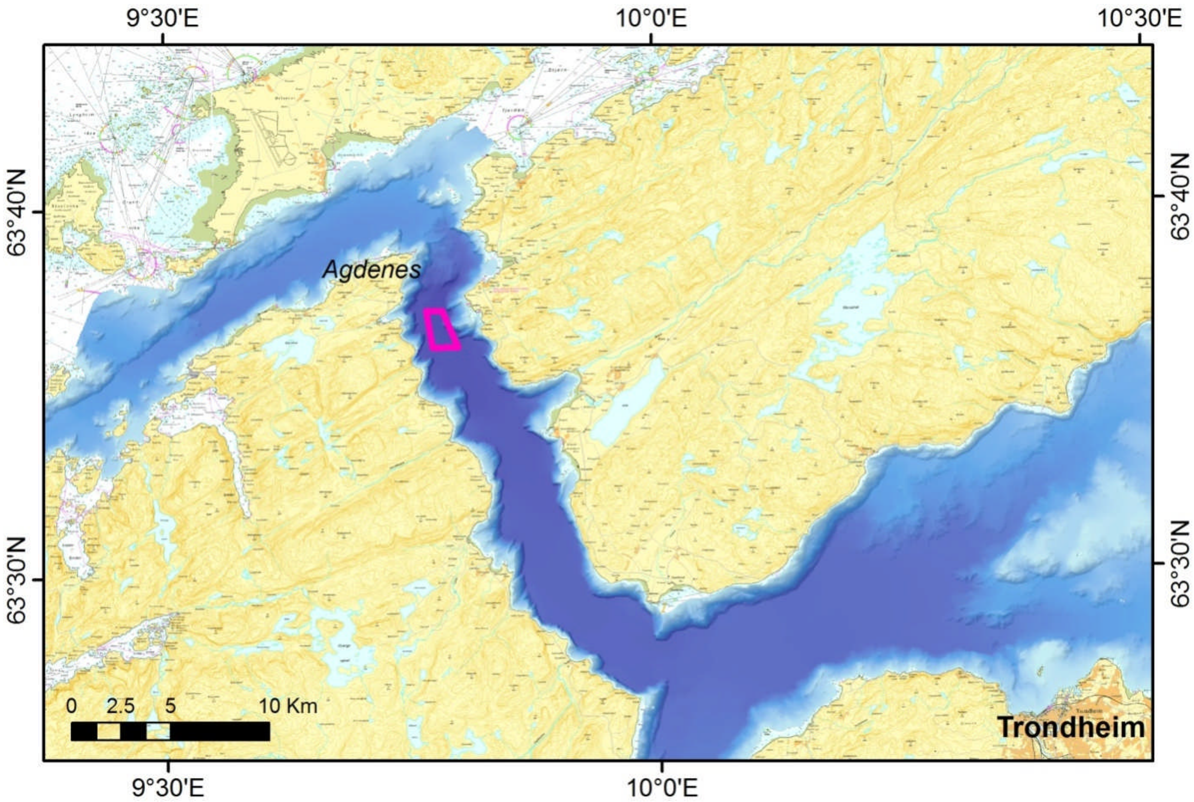


Figure 7. Location of the dumping ground survey site off Agdenes in Trondheimsfjorden where the water depth is around 600 m.

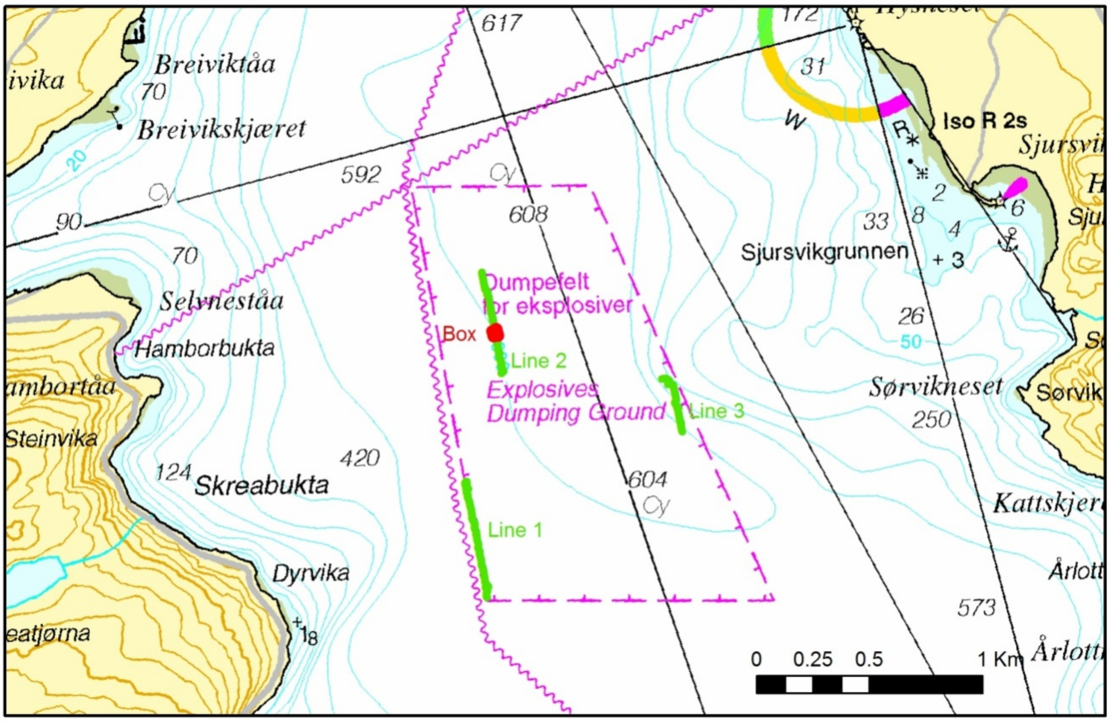


Figure 8. Position of the 3 survey lines and box survey within the dumping ground (see Figure 7 for location).

3.2 Equipment

3.2.1 ROV

The UHI was mounted on NTNU's working class ROV, a Sperre SUB-fighter 30K (Figure 9) which is capable of working at the depths (600 m) and underwater conditions of the study site, which is prone to strong currents (see section 3.1). The ROV had received a significant overhaul as preparation for the survey, and Ecotone was involved with the planning and finalization of the upgrades to ensure reliable UHI communication and secure the imaging system along with light sources (2 x 250 Watt halogen lights from DeepSea Power & Light) in appropriate mounting brackets. The ROV was also equipped with an HD-video camera mounted at the front.

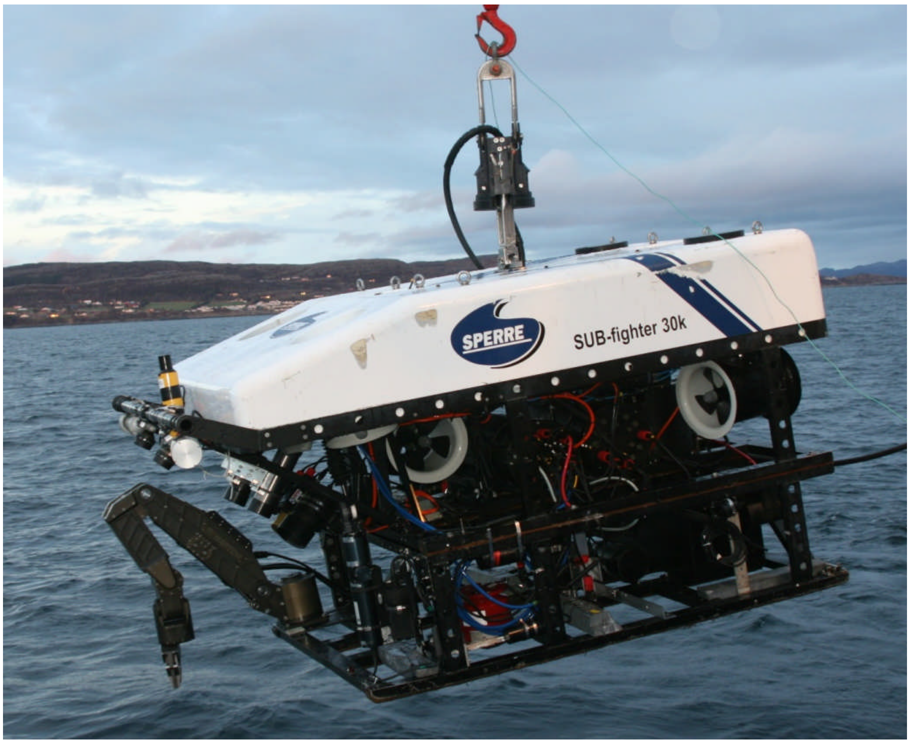


Figure 9. The working class ROV, owned and operated by NTNU, with the UHI mounted in the middle of the ROV frame.

3.2.2 UHI

The UHI was mounted in the centre of the ROV, giving an unobstructed field of view of the seafloor as well as protection from any impact. The light sources were fixed and flank the UHI at 35 cm to each side. This provided even illumination of the field of view at the expected altitudes for the planned surveys. The field view of the UHI was 1:1 with altitude. The UHI was connected to the ROV via a four-pin (two fibre optic, two power) hybrid umbilical cable, which provided both the data connection and power supply. The UHI was controlled from the topside and the data were transmitted to, and stored on, the computer on board the ship. Precise manoeuvring of the ROV, far superior to that obtainable by manual piloting, was achieved by using a dynamic positioning system developed at AUR-Lab (Ludvigsen et al. 2014). This system allows the ROV to stay on station and track lines with errors of less than 10 cm relative to the references.

A stable platform is essential for producing high quality UHI images. The line scanner acquires between 20 and 50 lines per second, and as such is very susceptible to movements which is why precise manoeuvring is so advantageous. Measurement of the UHI movement is obtained from the ROV's navigation sensors. The position, pitch, roll, heading, depth and altitude are recalculated to the UHI's position relative to the sensors. This information is later used in geocorrection when processing the UHI imagery. The acoustic positioning system of the ROV and ship provides the position of the ROV (and UHI). The data are consolidated in navigation files with filtering applied to remove outliers if necessary. An overview of the surveyed areas are given in Table 1 with comments on any more general operational issues related to each line. Further operational issues are noted below.

Table 1: Overview of surveys performed during fieldwork. Coordinates UTM 32N (WGS84).

Survey	Date and time	Start	Stop	Operational Field Notes
Line 1 (500 m)	Dec 10: 11:11-12:28	7053153.081, 538323.990	7053156.097, 538322.132	Restarted at 11:11 due to CTD recovery
Line 2 (500 m)	Dec 10: 14:01-15:56	7054546.882, 538302.897	7054099.866, 538391.819	
Box (20 x 25 m)	Dec 10: 16:54-18:46	7054264.084, 538374.114	7054261.425, 538354.786	The ROV performed alternate transects backwards to counter the current
Line 3 (500 m)	Dec 11: 09:49-10:53	7054048.242, 539150.382	7053838.559, 539191.392	UHI recording difficult and cut short due to currents and umbilical problems. Standard classification not possible due to inaccurate logging in these conditions. Vertical mapping was not possible at this point.

3.2.3 Field annotation of benthos and bottom type

During video and UHI recording along the survey lines, time-stamped observations of benthic invertebrate taxa, demersal fish and bottom type were recorded using the annotation software CampodLogger (developed at IMR). Observations of seabed biology and geology were logged in parallel by scientists from IMR and NGU respectively based on video data, as is standard practice under MAREANO video surveys. Biology logs recorded occurrences of organisms (both at species level or at higher taxonomic levels), but when organisms occurred too frequently it was not possible to record everything. All changes in sediment type were logged, together with comments on any objects of interest (e.g. bombs, garbage, etc.).

The CampodLogger software is designed to log navigational data (date, UTC time, positions and depth) in an NMEA standard along with records of bottom types, fauna and any other comments. Unfortunately during this cruise it was not possible for the laptops running CampodLogger to get access to such navigational data from the vessel and the ROV. Therefore, logged data were only time-stamped and needed to be matched up with navigational data after the survey. This process was further complicated by the fact that clocks could not be automatically synchronised at the start of the survey lines. Nevertheless, satisfactory corrections have been made in post-processing such that biological and geological observations were adequately georeferenced and accessible via GIS. Matching these observations with UHI images required further adjustments of timing and positions and does not always appear to have been successful (see section 5.4).

3.2.4 General operational issues

NTNU's ROV had the capability to meet all the needs of the UHI, however, the umbilical reached its maximum length on several occasions during the surveys. Drag on the umbilical through 600 m of water was also a problem. This occasionally led to the ROV veering off course, especially when moving further from the ship or when currents were strong. As a result of these problems parts of the UHI data were dominated by spatial stretching.
The ROV experienced some further operational challenges related to the depth and current conditions during the survey. There were occasions where the ROV was halted during the transects due to straying too far from R/V Gunnerus, which required the ROV to wait for the ship to catch up with the umbilical. In the extreme cases, the drag on the umbilical caused the ROV to be pulled suddenly back and upwards. As the UHI is a push-broom line imager, movements of the ROV (in all directions) have an influence on the resulting UHI data. Geocorrection will correct for the movement of the ROV and adjust the images accordingly, but only to the degree that the logging sensors can record. Sudden jolts, current influx and the subsequent counter-manoeuvres are known to be particularly challenging in the post-processing.

Challenges related to logging data and operating the ROV influenced the geocorrection of UHI images. As it is a line-scanner recording between 20-50 frames per second, time synchronization and accurate navigation logs are necessary to produce optimal results. There was no time server on the survey, so the computers were synchronized manually. This appears to have had an effect on the overall image correction. The same can be said for the fact that the ROV often would swerve sideways, make sudden stops due to short umbilical or currents. When UHI images appear skewed, it is most likely due to the ROV manoeuvring back on track or at angle to counter the water masses or the short umbilical. Automated synchronization is recommended for future surveys.

4. POST CRUISE DATA ANALYSIS AND INTEGRATION

4.1 UHI data processing

The data were processed using Ecotone’s proprietary software for radiometric calibration and apparent reflectance measurements. This process corrects for internal (sensor) and external (water column) influences on the hyperspectral image, and aims to present the apparent reflectance values of the objects in the image. Ecotone uses a 3D radiative transfer theory model to calculate light scattering and absorption. The position of the lamps during the survey were entered into the model and subsequently used in the reflectance processing. Accurate altitude and pitch/roll measurements are essential in this process, to ensure quantifiable data across the different data files and transects. This process has proven to work well with the underwater light models used in this study. The radiometric and reflectance processing required approximately four hours per transect (both 500m lines and box transect) when run on a standard Intel® Core™ i7 laptop.

The UHI images were geocorrected using the ROV navigation logs. This process involves assembling the lines in the order and position in which they were acquired, and adjusting for ROV movement to ensure accurate coordinates for each pixel, and thus, OOI. The ground cover for a pixel after geocorrection varies with altitude. An example of a log file used in geocorrection is shown in Figure 10. Filtering has been applied to the positioning data to remove outliers or false data points (e.g. the ROV jumps 5 metres in one second).

```
;UHI Navigation File
;UTM Zone 32 N
 10-12-2014  10:42:00.0009  7053103.926 538326.9087 1.163104    4.194051    -48.959244  584.32685   1.1596
 10-12-2014  10:42:00.1419  7053103.939 538326.8692 1.254778    4.314372    -50.053593  584.309245  1.1602
 10-12-2014  10:42:00.2599  7053103.952 538326.8305 1.266237    4.4748      -51.291182  584.288181  1.1643
 10-12-2014  10:42:00.4239  7053103.966 538326.7928 1.294885    4.543555    -52.471475  584.2664    1.1715
 10-12-2014  10:42:00.5679  7053103.981 538326.756  1.174563    4.967544    -53.583013  584.238568  1.1816
 10-12-2014  10:42:00.7359  7053103.986 538326.7307 0.790682    4.560744    -55.490962  584.219637  1.2001
```

Figure 10. Example log file for use with geocorrection, in this case from Line 1. In the columns from left to right: Date, Time, Position (N, E), Pitch, Roll, Heading, Depth and Altitude. The log data have been resampled to 7 Hz (i.e. 7 logs per second) by AUR-Lab.

Additional corrections were applied to fix image artefacts. Acoustic underwater positioning can often be off by a few metres. For this reason, the navigation logs require post-processing to eliminate invalid data points, so that they do not influence the geocorrection. For example Figure 11 shows the UHI file before (a) and after (b) smoothing of the navigation data used for geocorrection, which effectively removes the artefacts visible in (a).

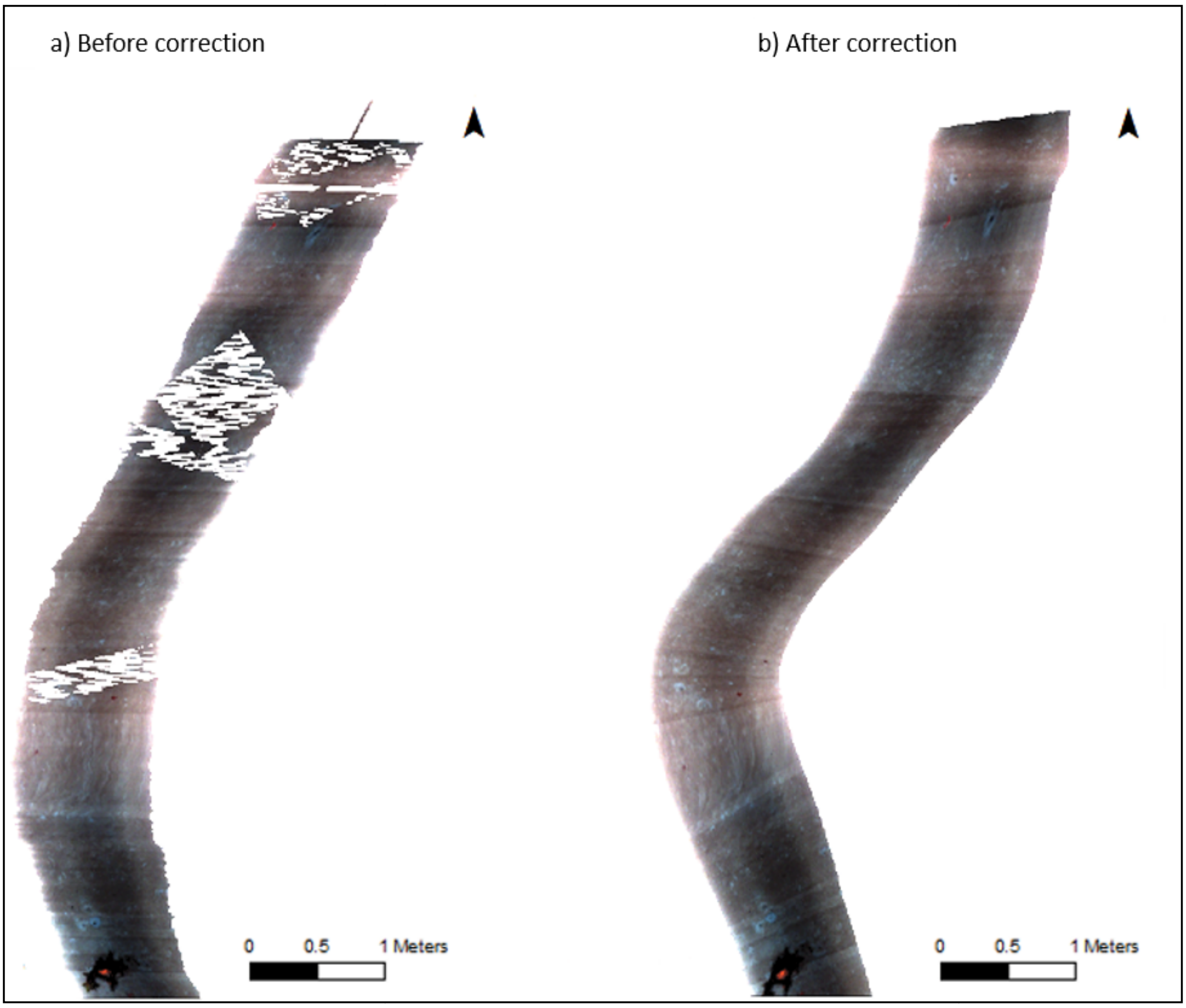


Figure 11. Excerpt from Line 1, showing the UHI file before (a) and after (b) smoothing of the navigation data used for geocorrection. The artefacts in A have been eliminated.

Following all data processing and corrections georeferenced RGB images were produced for each line and the box survey area suitable for direct display in GIS.

4.2 UHI data classification

Classification of UHI data is performed in order to identify and highlight particular OOIs or seabed types based on their spectral characteristics. Automated classification of images using spectral information is one of the major benefits of UHI commercially marketed by Ecotone and the focus of much of their development activity. Automated classification could offer potential benefits for MAREANO if it can contribute to a reduction in time required for detailed analysis of video data and/or provide more certain results than expert visual interpretation and was therefore an important part of the evaluation exercise.

Classification of the present dataset was performed using both commercially available and Ecotone in-house developed spectral processing software. At the time of the survey and the subsequent post-processing, Ecotone's standard processing route employed the commercial software ENVI 5.2, using both standard built-in tools and Ecotone's own developed extensions. ENVI was therefore the main tool used for OOI classification and production of classified UHI maps, but several iterations of the Ecotone internal software development have been applied to the dataset during the course of this project. Both these methods used spectral information from UHI data as the basis for classification, not just simple visual differences from RGB versions of the UHI data.

Classification in ENVI was performed using the results from Spectral Angle Mapper (SAM). This algorithm determines spectral similarity by calculating the spectral angle between the spectra of interest and the reference spectra, by projecting them as vectors in a space with dimensions corresponding to the number of bands (Figure 12) (Sohn and Rebello 2002; Kruse et al. 2003). One great advantage of SAM is that it is insensitive to changes in illumination between the compared pixels. Darker pixels will fall closer to the origin point than illuminated pixels, but the angle between the vectors is still the same. It should be noted that the default SAM in ENVI does not include spectral variability within the classes, instead using one reference spectra for each class (Kruse et al. 2003). Classification using SAM in ENVI on a standard Intel® Core™ i7 laptop required approximately 12 hours per 500m line and 30 minutes for the box transects. The files from the box transect are combined into a mosaic file and processed all at once, resulting in the much shorter processing time.

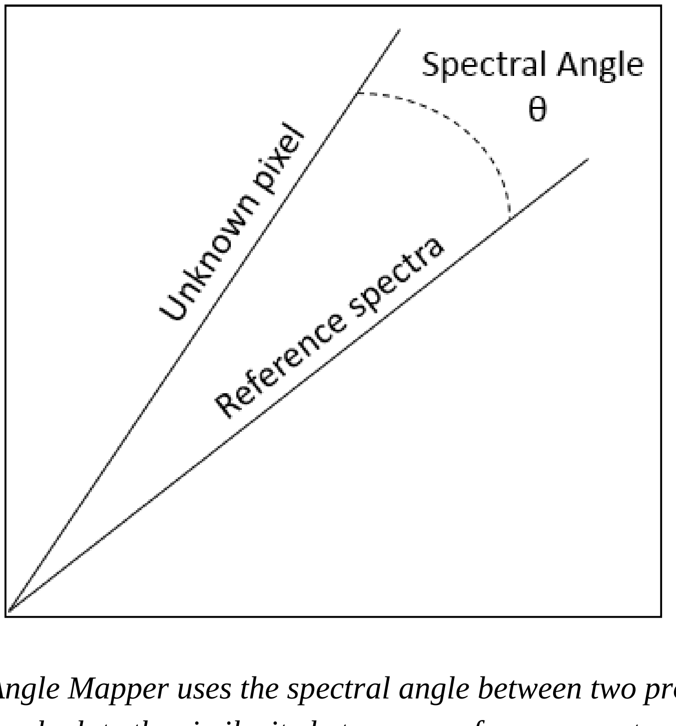


Figure 12. Spectral Angle Mapper uses the spectral angle between two projected vectors in n-dimensional space to calculate the similarity between a reference spectra and an unknown class (Sohn and Rebello 2002).

The reference spectra were created by selecting a group of pixels covering the OOI. This is done manually in ENVI and therefore relies to some degree of expert knowledge to identify the relevant pixels. An average of all the pixels for one class (OOI) was stored as a spectral signature in a spectral library file. This file was then used as a reference when SAM performed the classification. If the projection of an unknown pixel was within the spectral angle of a reference spectra, it was assigned to that class.

The spectral angle can be adjusted to match the data distribution. A default value is applied to all classes, but each class can be manually adjusted. This is necessary to minimize class contamination, especially when working with rare classes where an increased angle can quickly include pixels from other similar objects (false positive). This is performed manually at this stage, and the user adjusts the angle for each class after evaluating the results.
In addition to using standard software tools for conventional remote sensing (i.e. ENVI), Ecotone is developing a specialized software for underwater hyperspectral imaging analysis. The software suite is currently on an experimental level, but to demonstrate some of the future possibilities, it was decided to also use some of these functionalities on some of the data in the current project.

One method used is based on Principal Component Analysis (PCA) (Pearson, 1901). The spectral components are decomposed into eigenvalues and eigenvectors. One can then disregard spectral components that are not important (associated with e.g. high frequency white noise). Some examples are given in section 5 to show how this method can be used to focus the analysis on spectral components relevant for sediments, or biological organisms with useful information. Another development is the use of Bayesian network models for classification. This is discussed further in section 6.5.

4.3 Data integration in GIS

The ROV navigation and UHI data were suitable for integration in GIS. Annotated logs detailing the geology and biology of each ROV dive were incorporated in GIS, while video data acquired in parallel with the UHI surveys were reviewed separately. ArcGIS 10.2.1 was used as the primary software for data integration and evaluation by MAREANO and several existing datasets were reviewed in GIS in connection with the UHI data. These included multibeam bathymetry data and two datasets acquired using a Kongsberg HUGIN AUV by The Norwegian Defense Research Establishment (FFI) in 2013 (Ludvigsen et al., 2014) (a) data from High resolution Synthetic Aperture Sonar (Kongsberg HISAS 1030) and (b) still black and white photo images. The multibeam bathymetry data were acquired by The Norwegian Hydrographic Service in 1999 using an EM1002 multibeam echosounder. Whilst these data, gridded at 5 m resolution, reveal the general bathymetry of the fjord they are low resolution in comparison to the details captured by the HISAS 1030 data (Figure 13).

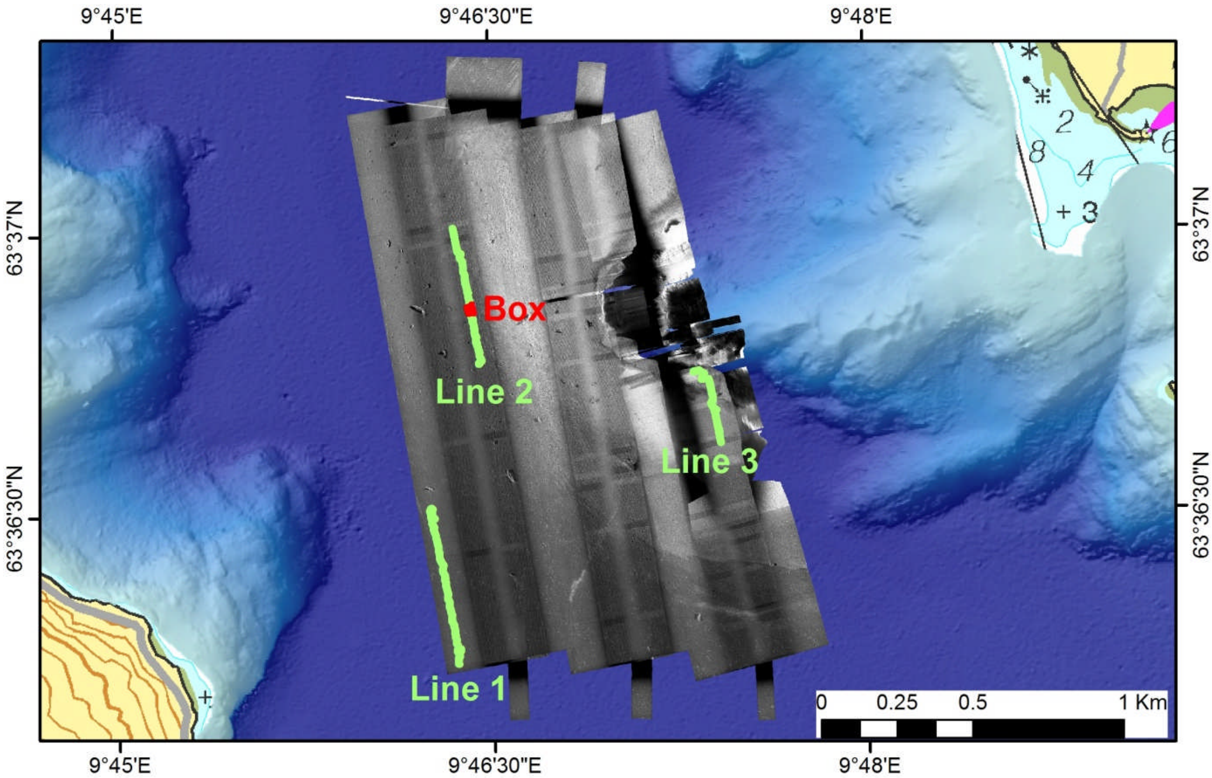


Figure 13. Existing multibeam bathymetry (5 m resolution) and AUV/ROV acquired data for the current survey area. The location of the three UHI line surveys are shown in green and the box survey in red.

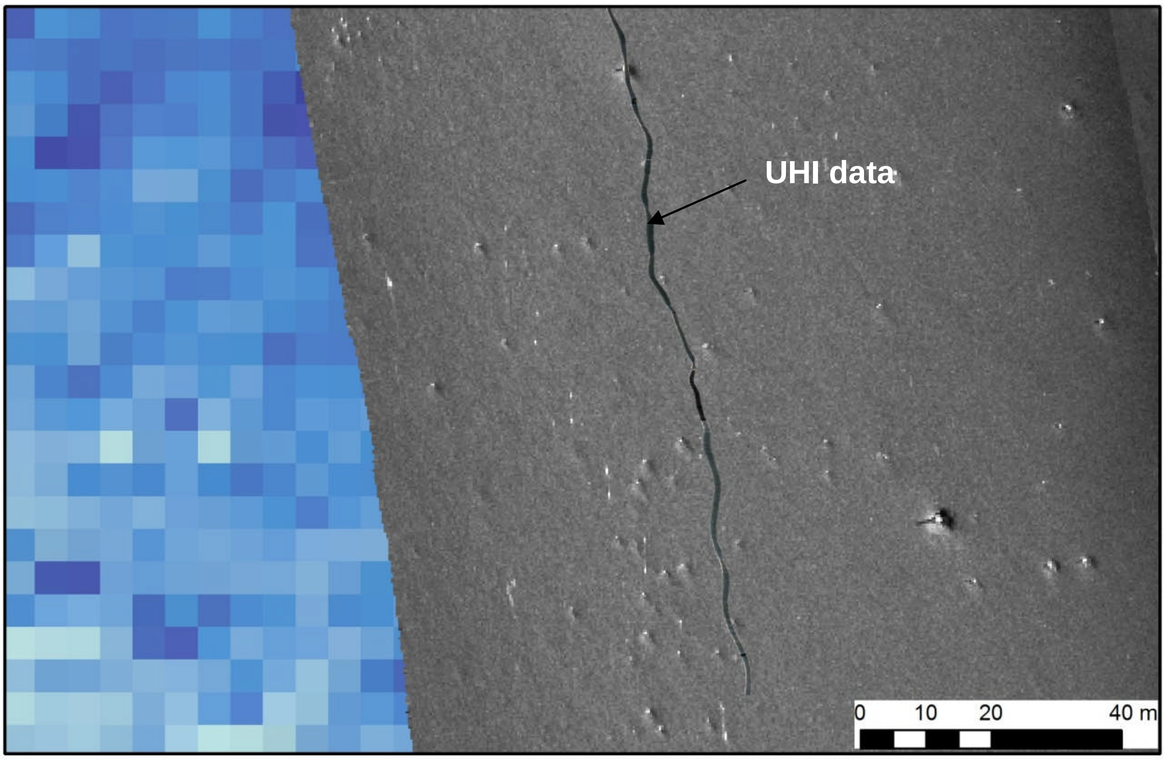


Figure 14. Example of multibeam bathymetry (5 m resolution), HISAS 1030 (33 x 33 cm resolution) and UHI data from the southern end of Line 1. Map scale 1:1000.

Examination of the data from Line 1 provides a good example of the different levels of detail captured by the various datasets. We see the 5 m multibeam data is pixelated at this zoom level (1:1000) and provides little information (Figure 14). The HISAS 1030 data, shown here gridded at 33 x 33 cm, by contrast, provide a lot of information about the variation in acoustic response of the seabed in far greater detail than can be obtained with shipborne multibeam (Thorsnes et al. 2014). When coupled with appropriate ground-truth data this means that HISAS reflectivity data can be invaluable for detailed sediment mapping and investigation of bedforms and/or objects on the seabed. High resolution bathymetry data can also be extracted from the HISAS 1030 data. At the present time the processing of these data require more computing resources than is practical for FFI to make the processing of the data standard practice. However, some data have been obtained from the 2013 dataset which demonstrate the very high resolution bathymetry that is possible to achieve with the HISAS 1030 (Figure 15). Use of HISAS 1030 and other AUV acquired data are currently being evaluated as part of a related MAREANO methods development study – see Thorsnes et al. (*in prep*).

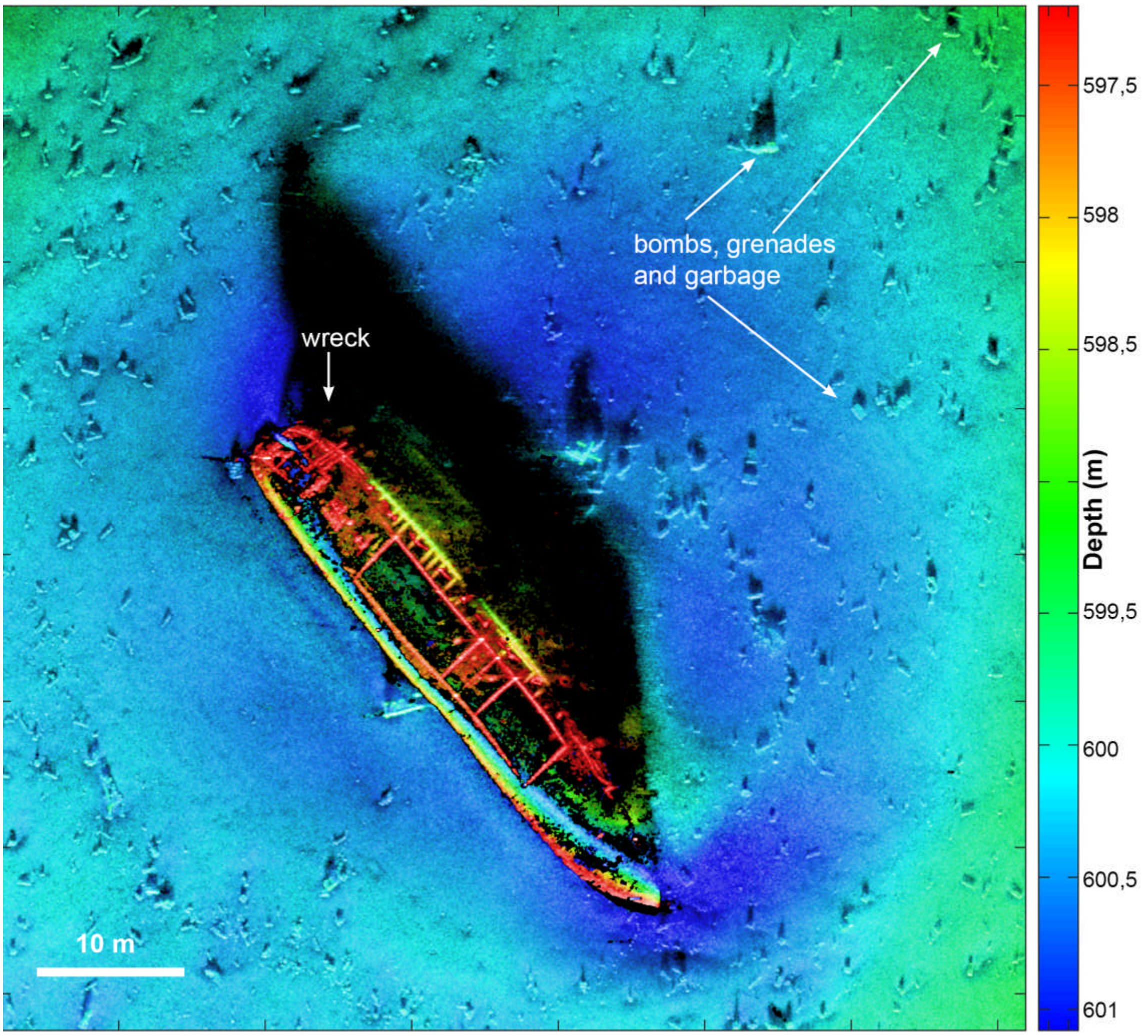


Figure 15. Image of ship wreck, bombs, grenades and garbage. The image was produced by combining interferometric bathymetry (grid size 2x2 cm) with despeckled sonar imagery (resolution 9x9 cm) from the synthetic aperture sonar HISAS 1030. Image courtesy: Torstein Olsmo Sæbø, Norwegian Defence Research Establishment (FFI).

Zooming in still further, we gain an impression of the level of detail that the UHI data are capturing. The UHI data are shown together with a 4 x 4 cm (full) resolution version of the HISAS 1030 data with RGB data shown in Figure 16 and classified data shown in Figure 17, both of which are at an image resolution of 0.5 cm. Further zooming on parts of the data shows the full resolution (Figures 18 and 19).

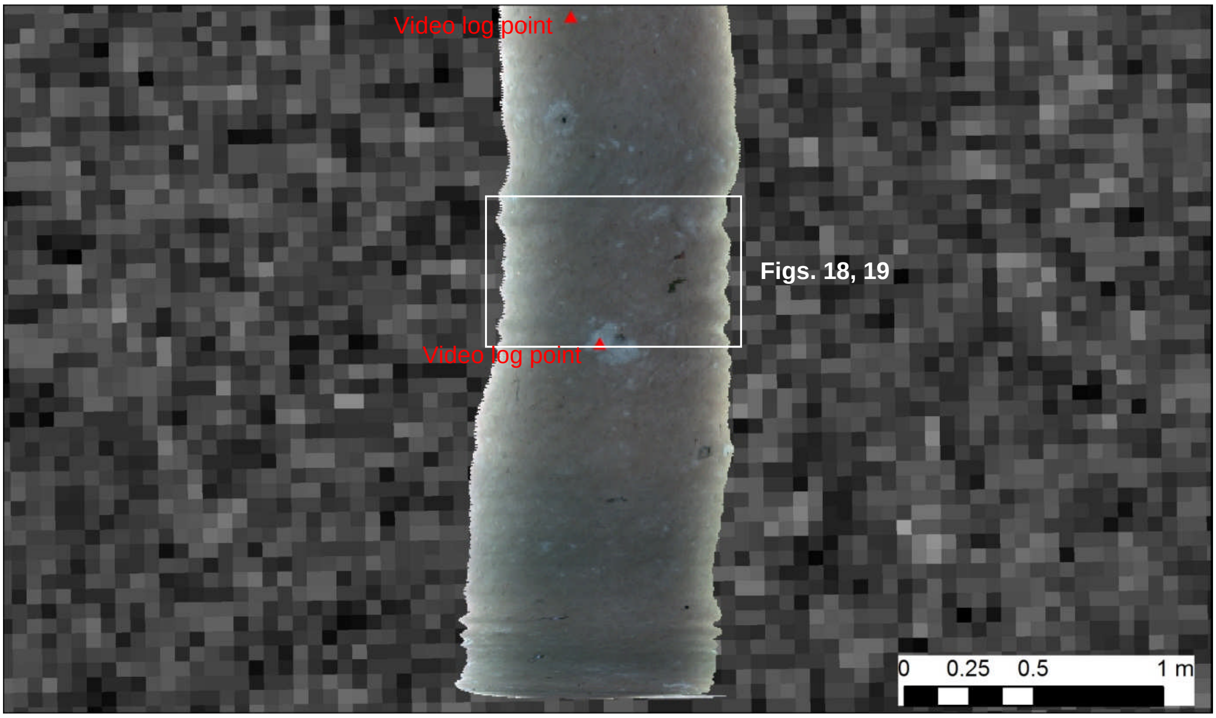


Figure 16. Example of HISAS 1030 (4 x 4 cm resolution) and RGB UHI data from the southern end of Line 1. Map scale 1:25. The red triangles indicate the position (time) bottom type observation logged by the geologist onboard. This gives an indication of the level of detail captured by UHI data and standard online video logging though it is important to note that the geologist is aiming to log the dominant bottom type, not centimetre level variations. The dominant sediment type is logged via the CampodLogger software by selecting a new bottom type when a change is observed, otherwise the currently selected bottom type is auto-logged every 10 seconds and comments are added where features such as burrows are observed. In this example the sediment type logged by the geologist is the same between the two red triangles, and the presence of burrows was noted. Where applicable for the mapping task in hand post-cruise analysis of video allows more detail to be captured, similar to that obtainable from UHI-RGB images.

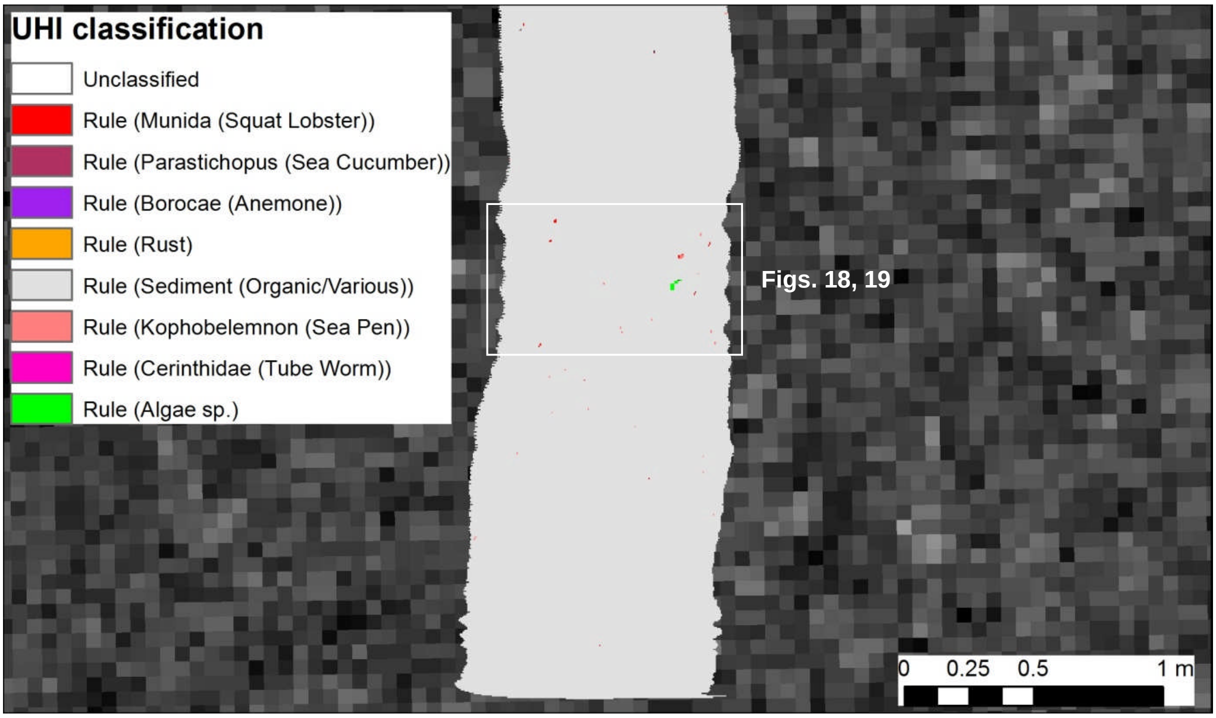


Figure 17. Example of HISAS 1030 (4 x 4 cm resolution) and classified UHI data from the southern end of Line 1. Map scale 1:25. Note that the UHI classification is focussed only on biological OOIs and therefore no distinction is made between undisturbed sediment and burrows.

The level of detail revealed by UHI RGB images is similar to that captured by standard video or photo surveys. Just as post-cruise video analysis is able to examine detail by controlling the speed of playback and freezing frames, more information can be extracted from the RGB data by zooming in on and panning through the RGB images in GIS. It is, however, important to note that, in contrast to photo/video images, the image resolution of UHI data does not correspond to the resolution limit of the information content. Spectral analysis reveals information related to objects physical characteristics, based on the reflected light. The aforementioned UHI RGB images are processed with only three wavebands for visualization purposes, whereas the UHI images with full spectral resolution will have the entire spectrum available per pixel. It is this spectral information which is used for image classification purposes.

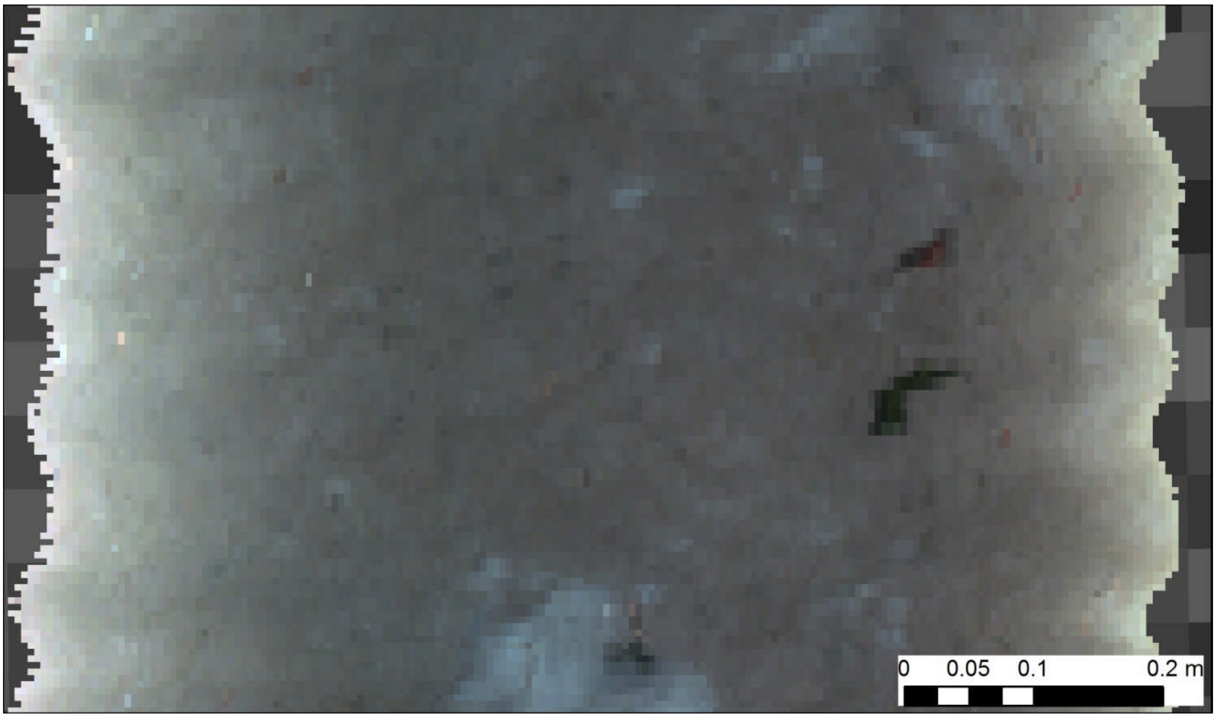


Figure 18. Example RGB image showing full detail Map Scale 1:5

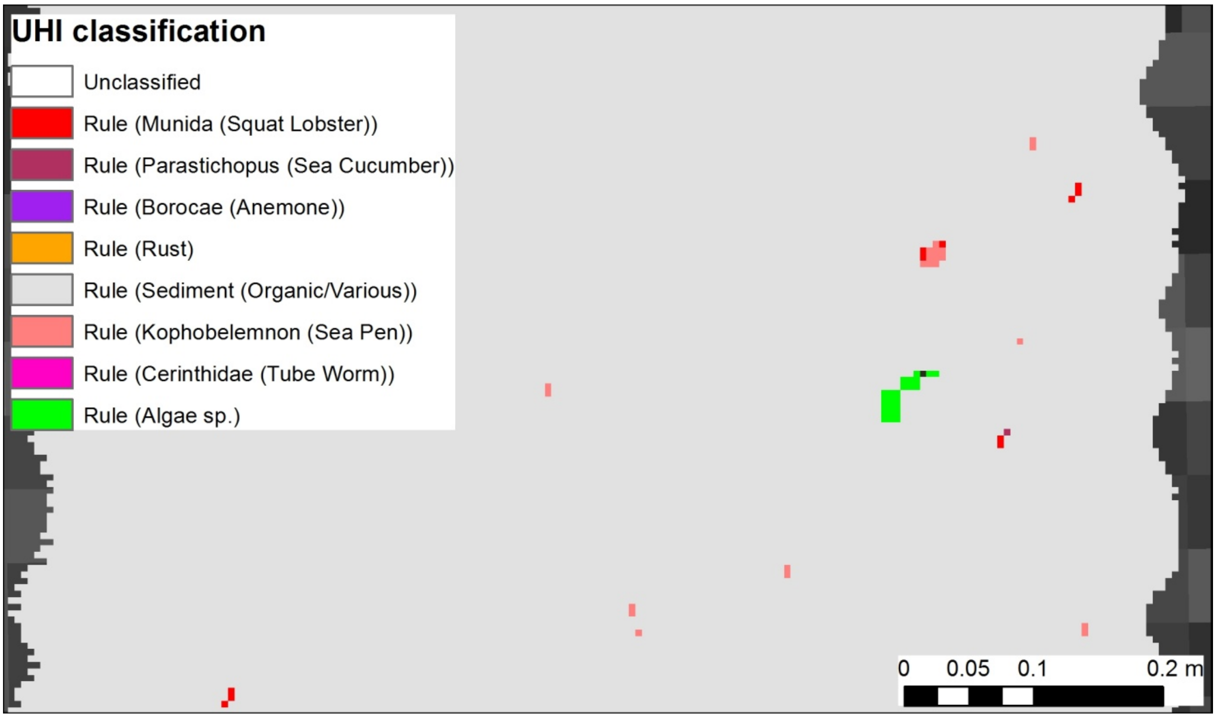


Figure 19. Classification of UHI from area shown in Figure 18. Map Scale 1:5. As in Figure 17 note that the UHI classification is focussed only on biological OOIs and therefore no distinction is made between undisturbed sediment and burrows.

5. MAREANO evaluation of UHI data

This section describes evaluation of the UHI data from this pilot project with respect to potential use of UHI in general for MAREANO mapping and related tasks. Note that MAREANOs assessment of UHI data focuses on the data as a basis for seabed mapping/species identification. We have not attempted to produce any actual maps based on the data as the study area is too small to allow this at scales relevant to MAREANO (1:100 000 and greater) and map production is outside the scope of this evaluation. Selected examples of data are shown in this section and the reader is referred to Appendix 1 (Ecotone report) for further data examples from this study.

5.1 Evaluation of UHI data aquisition

The UHI performed as required with no technical issues or downtime due to UHI operations. Both the ROV-pilots and NTNU's dynamic positioning system worked as expected to provide as good recording conditions as possible for the UHI, as well as adjusting camera focus and position to provide optimal HD-video for the video loggers.

Although adequate for a pilot study, even this work-class ROV however does not appear to be an ideal platform for the UHI, particularly in more challenging sea conditions. Problems with the umbilical and sudden manoeuvres of the ROV led to artefacts in the UHI data that are challenging to correct for in post-processing. Automated synchronization of survey computers also seems to be of primary importance to ensure optimal UHI data quality and this was, unfortunately, not available during this cruise.

UHI data acquisition so far remains untested using a towed underwater platform such as IMR's CAMPOD/Chimaera currently used as standard in MAREANO surveys. Towed platforms like this offer no control over the exact path followed and are very susceptible to swell. It remains unknown how much the inherent movement of such as towed platform would affect UHI data but it is likely to be challenging and require additional post-processing to overcome motion during data acquisition, although may be less problematic using the latest [2016] UHI system (see section 6.5). Towed platforms should be less prone to sudden movements than an ROV once at a constant altitude as they cannot change course, however sudden changes in topography mean sudden vertical movements as the winch raises the video-rig.

MAREANO has recently begun investigating the use of AUV for seabed mapping and has conducted a pilot study using FFIs HUGIN AUV in autumn 2015. Experiences from this cruise and post-cruise analysis of data will be used to evaluate the general usefulness of AUV-based surveys for MAREANO mapping (Thorsnes et al., *in prep*). Sensors used in this 2015 pilot study did not include UHI but, as discussed earlier, AUV platforms can offer several benefits in terms of stability and precise navigation which would allow better UHI data to be acquired.

Independently, Ecotone as a partner of the MarMine research project (http://www.ntnu.edu/igb/marmine), has during spring/summer 2016 developed and integrated the UHI on a HUGIN class AUV in depths of around 2900 m (see section 6.5.1).

5.2 Evaluation of UHI data suitability for spatial integration with standard MAREANO and related data

Processed UHI data were provided by Ecotone in the form of georeferenced image files. Both the RGB (.bsq files) and classified (.dat files) UHI files are precisely georeferenced and can be visualised in desktop GIS. The data are therefore, in theory, relatively easy to integrate with integration with multibeam data and higher resolution HISAS 1030 data. The scale mismatches between the multibeam and UHI data limit the usefulness of interpreting these data in tandem, however. The finest resolution multibeam data available inTrondheimsfjorden were 5 m pixel size, and this is in keeping with the standard bathymetry data resolution currently delivered to MAREANO by programme partners the Norwegian Hydrographic Service. MAREANO often has access to multibeam backscatter data at finer resolution, typically 2-3 m, but even this resolution is far from the 0.005 m resolution of UHI data. The HISAS 1030 data (4 - 33cm resolution) provide an ideal link between the multibeam and UHI resolutions on this particular survey but HISAS 1030 data are not a part of standard MAREANO surveys, and the lack of data at an intermediate scale would make it difficult to relate the scales of acoustic and hyperspectral observations (see Figure 14), although this is equally challenging for standard visual observations (video).

The high resolution of the UHI data (0.005 m) makes the file sizes large and therefore slow to display and update in GIS. This is particularly cumbersome if interpreter needs to zoom frequently to gain an overview of the UHI data in the context of the lower resolution acoustic data. During Ecotone processing, the line surveys have been split into segments, often around 30 m long, but sometimes shorter, this results in relatively long rasters where the data coverage is only along the central section, the remaining area being NoData (Figure 20). Smaller (i.e. squarer), segments may facilitate more efficient display of files. The down-side of this is handling (e.g. symbolisation) of a large number of files, becomes more demanding. GIS-based solutions for handling multiple raster (image) files such as ArcGIS mosaic dataset may also be an option to make handling of multiple files easier for the user (this is an approach currently being implemented at NGU for handling of acoustic raster data and also has many terrestrial applications e.g. aerial photograph management).

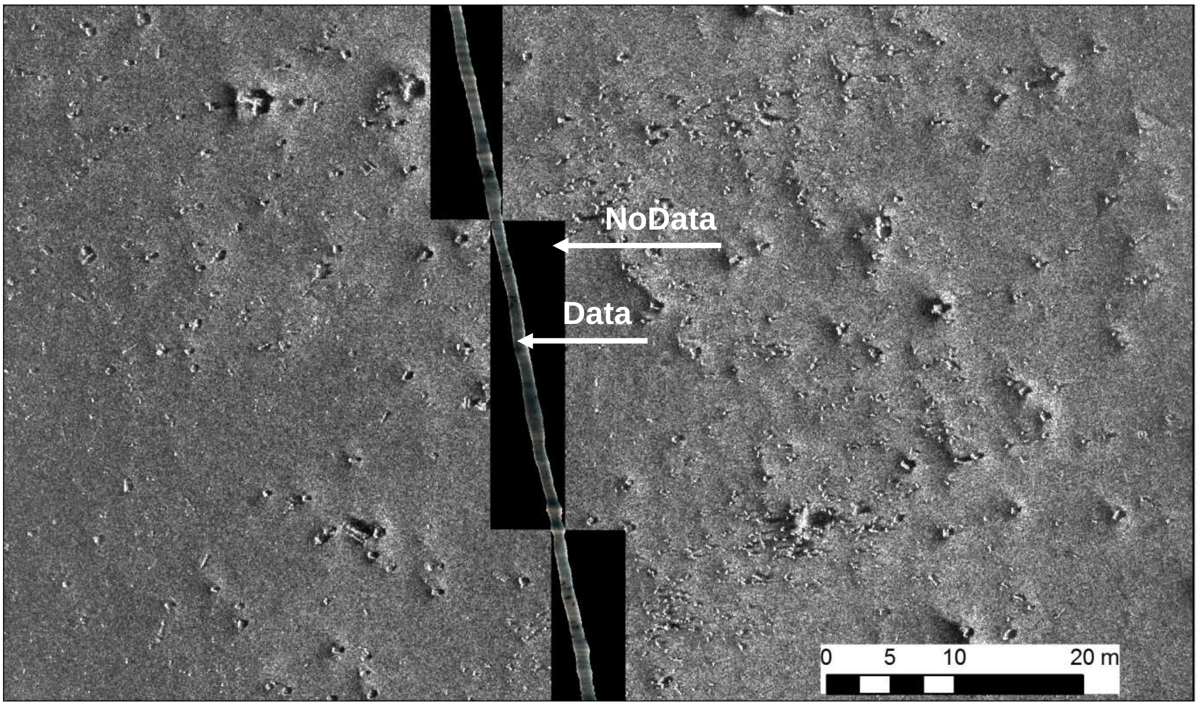


Figure 20. Extent of data (RGB) and NoData (black) for each UHI line section.

Raw UHI data cannot be accessed through standard GIS and have not been available for MAREANO testing directly as part of this study. Access to raw data has, however, been demonstrated to MAREANO scientists at Ecotone's premises in Trondheim. Through the course of these discussions it was identified that there are several features, (e.g. GIS-based access to spectral information) that may be desirable for MAREANO scientists to have, through the use of appropriate software or GIS Add-ins. Such software development could potentially be done by Ecotone but at present their business strategy focuses on improvement of tailored classified data solutions rather than the provisions of user access to raw data, or a data interface facilitating user interaction with the data (e.g. querying spectral information, developing classifications of OOIs). This focus is not necessarily well matched with scientific (e.g. MAREANO) use of UHI data. It is also not particularly conducive to close collaboration with expert end-users for the expansion of spectral signature libraries.

Although not directly related to the UHI data we note here that on this cruise it was not possible to obtain direct position information to the MAREANO (biological and geological) video logging using CampodLogger during UHI data acquisition, even though CampodLogger input requirements were specified to Ecotone/AUR-Lab in advance of the cruise. This lack of directly recorded position information created difficulties in using the CampodLogger data in conjunction with the UHI and other datasets during post cruise analysis as only time information was logged, not position or depth. Adequate sampled position files were, however, created by Ecotone by merging the MAREANO logs with sampled ROV position data after the cruise. This allowed files with all information to be created and successfully displayed in GIS, additionally allowing corrections to be made for the field of view of the video camera relative to the ROV centre. This extra work would have been unnecessary had the correct connections and time synchronisation been available on board. Real time video logging with correct times and positions is a pre-requisite for any future surveys involving comparison or potential integration of video and UHI data (see also synchronisation issue in section 5.1).

5.3 Evaluation of UHI data for the identification of benthic organisms

As part of standard MAREANO procedure the identification of benthic organisms is done from video data as well as from physical samples (grabs, box core, bottom trawl and epibenthic sled). For the purposes of this report the identification of benthic organisms from UHI data is evaluated with respect to data from video only, not physical samples since no benthic samples were taken as part of this study and the methods are far less comparable.

The occurrence of benthic organisms (both at species level or at higher taxonomic levels) based on HD video observations was logged the field at three locations (Line 1, Line 2, and the box, see Figure 8) using CampodLogger. These results were compared with UHI data during post-cruise analysis. A total of 36 taxa -identified and un-identified species were observed and are listed in Table 2 where taxa identified to genus or species level are shown in italics and species identified to family level shown in regular font according to standard taxonomic notation, with ‘Indet.’ used after family name to denote indetermined species. Three of the species identified were uncertain and are indicated with a question mark. These species were rare in the area and require clearer images/less distance to object to enable confident identification.

Table 2: List of all plants and animals that were observed on video data during UHI surveys. Uncertain records are marked with "?"

Algae and kelp debris	
	Fucus serratus
	Laminaria hyperborea
	Saccharina latissima
Sponges	
	Antho dichotoma ?
	Axinellidae Indet
	Phakellia sp.
	Porifera Indet
Anthozoans	
	Actiniaria Indet
	Anthomastus grandiflorus ?
	Bolocera tuediae
	Cerianthidae Indet
	Drifa glomerata
	Funiculina quadrangularis
	Gorgonacea Indet
	Kophobelemnon stelliferum
	Paramuricea placomus
	Pennatulacea Indet
Polychaets	
	Polychaeta (Tubebuilding) Indet
Bivalve	
	Acesta excavata
Seastars	
	Henricia sp.
	Asteroidea Indet
Sea cucumbers	
	Bathyplotes natans ?
	Parastichopus tremulus
Crustaceans	
	Brachyura Indet
	Munida sp.
	Paguridae Indet
	Pandalidae Indet
Fish	
	Brosme brosme
	Chimaera monstrosa
	Teleostei Indet
	Teleostei small
	Galeus melastomus
	Lychenchelis sp.
	Molva molva
	Pleuronectidae Indet
	Sebastes sp.

Three of the taxa represented debris of seaweed and kelp, which had sunk to the seabed from the littoral and upper sublittoral, rather than being a natural part of the benthic community. It is uncertain to what degree their characteristic photo-pigment composition remains similar to live specimens. Excluding the dying algae debris, eleven species were identified (*Bolocera tuediae*, *Drifa glomerata*, *Funiculina quadrangularis*, *Kophobelemnon stelliferum*, *Paramuricea placomus, Acesta excavata, Parastichopus tremulus, Brosme brosme, Chimaera monstrosa*, *Galeus melastomus*, *Molva molva*). Of the unidentified species, six could be expected to represent single species: Axinellidae Indet, *Phakellia* sp., Cerianthidae Indet, *Munida* sp., *Lychenchelis* sp. *Sebastes* sp. Of these 17 species which are good candidates for studies of hyperspectral composition, nine were recorded more than five times in the video data (Table 3).

Table 3: Species suitable for studies of hyperspectral composition that were registered more than five times in video data.

Species	No of records
Cerianthidae indet.	152
***Munida* sp.**	71
Kophobelemnon stelliferum	50
Bolocera tuediae	49
Parastichopus tremulus	46
***Lychenchelis* sp.**	33
Drifa glomerata	26
Chimaera monstrosa	20
***Phakellia* sp.**	6

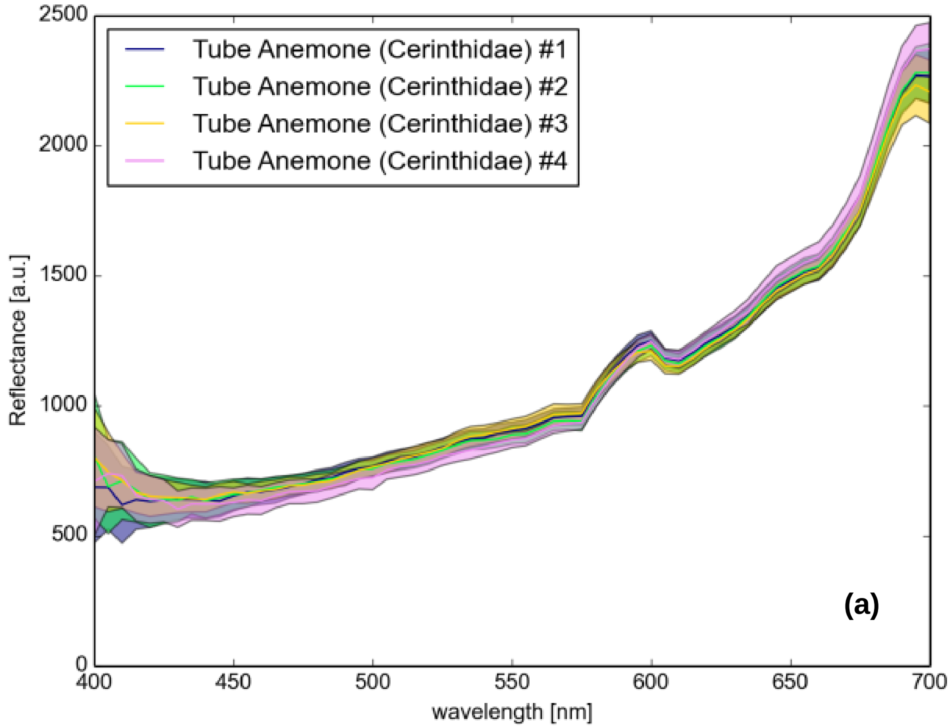
5.3.1 Spectral characteristics and intra-species consistency

The spectral characteristics of biological organisms can vary with shape, size and position of the organism at the time of image capture. This influences the spectral signature acquired from the organism, and thus it is necessary to account for the variation of the signature within a spectral library.

Whilst initial data processing and analysis by Ecotone (Appendix 1) provided only very limited spectral signature information for biological OOIs, results from the latest version of the Ecotone spectral analysis software (section 6.5, Appendix 2) includes the option to account for the variability in the spectral signatures. This was a development that was undertaken by Ecotone in direct response to the demand for this type of information at an early post-cruise meeting of MAREANO-Ecotone.

When plotting the spectra of individual specimens, the standard deviation of each band (wavelength) is displayed. This gives an indication of where in the electromagnetic spectrum the organisms show variability and similarity. Figure 21 displays examples of the spectral signatures and their measured spectral standard deviation for five common species [(a) tube anemone (b) red sea cucumber (Parastichopus), (c) deeplet sea anemone, (d) squat lobster, and (e) the gorgonian Paramuricea]. The first four of these organisms are all red and Figure 21f provides a direct comparison of the spectral signatures between species, in particular the spectral position of the peaks which is used to distinguish each species.

In general, the graphs (Figure 21a-e) show very similar signatures and overlapping standard deviations for the specimens of the same species, yet with characteristic signatures for different species of relatively similar colour (Figure 21f). Common for all species is a peak around 690 nm (the red end of the spectrum). Four of the species (all except the red sea cucumber) have an additional peak at wavelengths between 600 and 625 nm (the yellow to orange part of the spectra). The tube anemones (Figure 21 a), which are characterized by their deep purple colour on conventional video has the highest values of all with wavelengths between 500 and 570 nm. The red sea cucumber (Figure 21 b) has the highest reflectance of all species in the red end of the spectrum (around 690 nm). The difference between this tube anemone (Figure 21 b) and the deeplet sea anemone (Figure 21 c) is a higher reflectance of yellow and orange for the deeplet sea anemone. The squat lobster, with an orange appearance, has a lower reflectance in the red spectra than the deeplet sea anemone, and also lower reflectance in the yellow spectra than the the gorgonian coral, *Paramuricea*, which has a characteristic yellow to orange colour. Paramuricea, (Figure 21 e) has the lowest values of all example species at the red end of the spectrum, but has the highest values in the yellow part of the spectrum (around 600 nm) and again shows its own characteristic spectral characteristics. . These results are promising but represent only a sample of results based on a limited number of observations. Further verification of spectral signatures for each species across a range of environmental conditions will be required as part of further development by Ecotone.



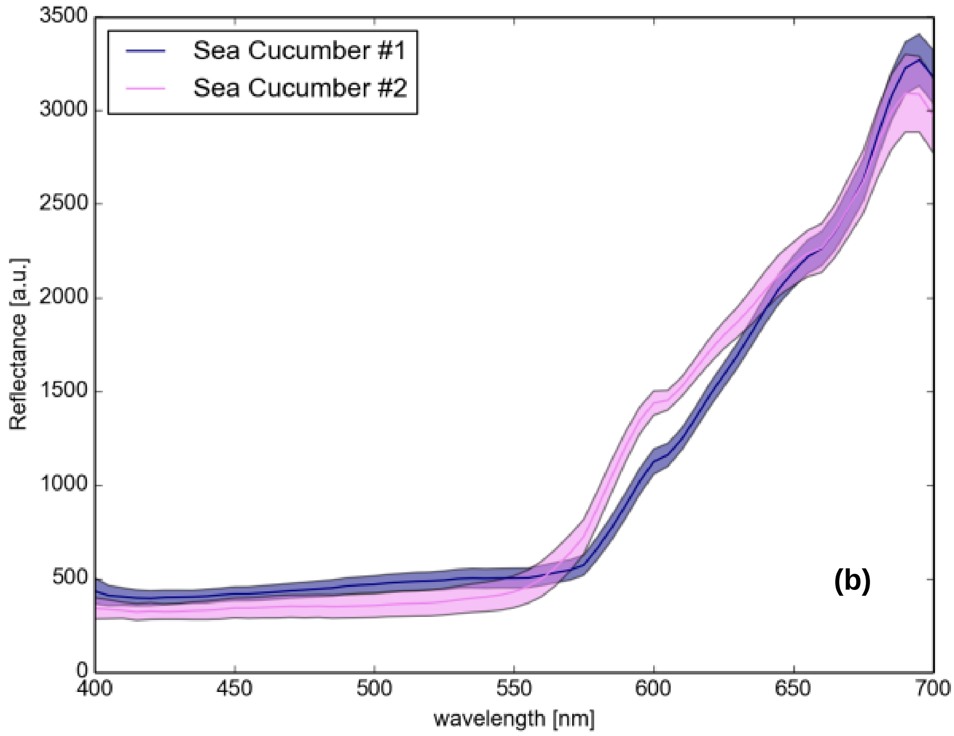
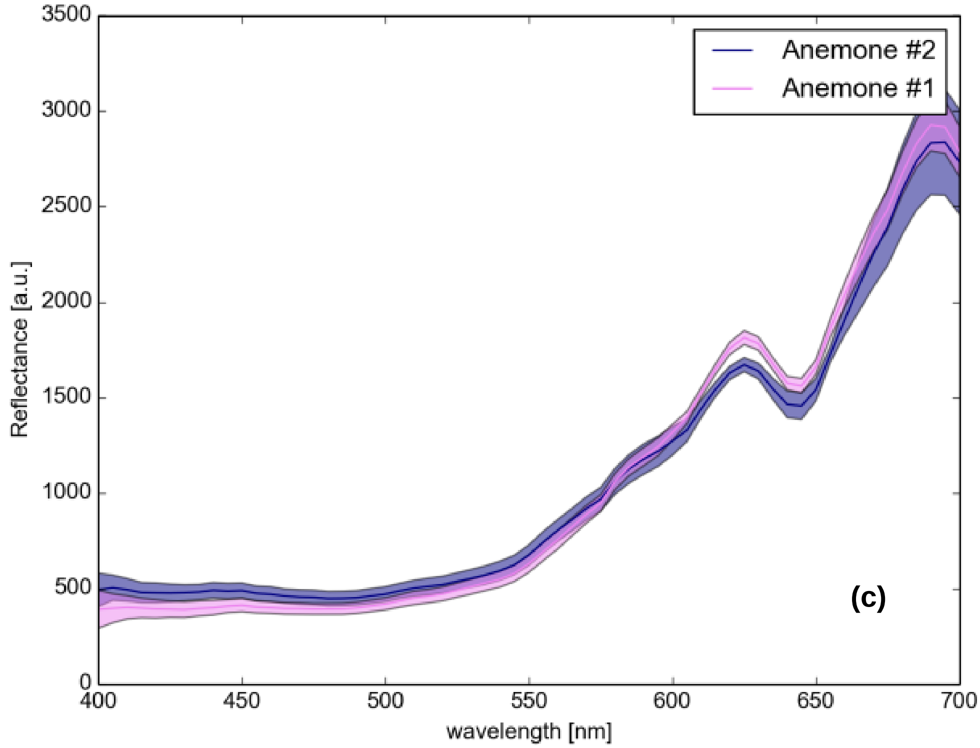


Figure 21. Spectral signature and standard deviation of five common species (a) tube anemone (b) red sea cucumber (Parastichopus), (c) deeplet sea anemone, (d) squat lobster, and (e) the gorgonian Paramuricea Comparison of the mean spectra from four of these species (f). Note that the vertical scales in each graph are not the same – scale ranges have been used to best highlight each spectral signature. (Figure continues on next page)



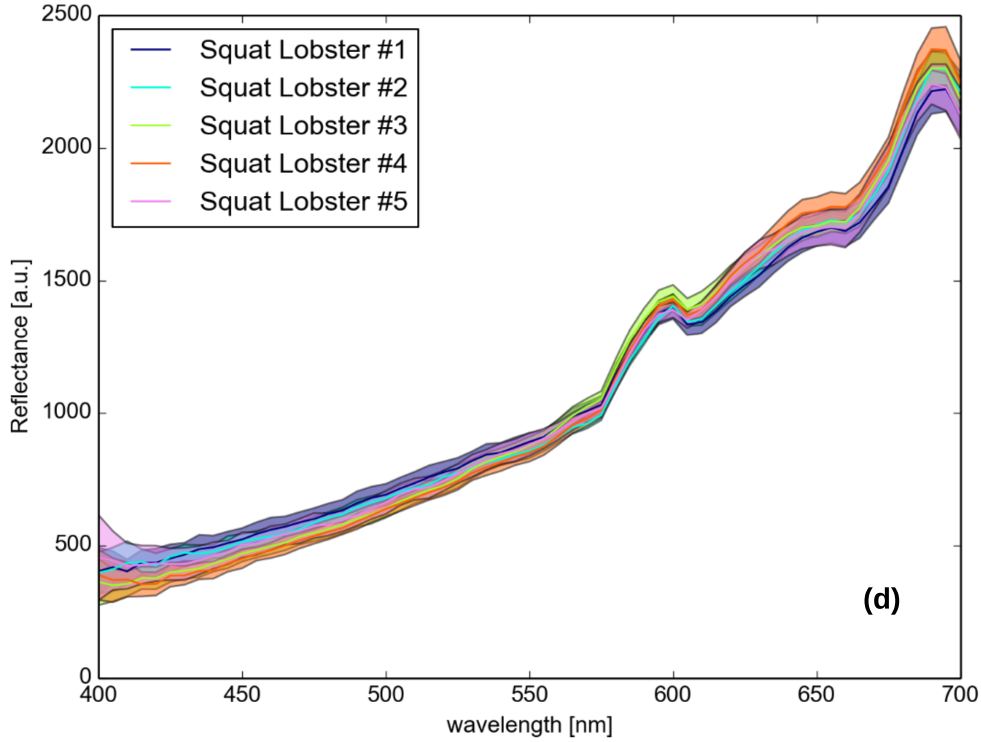


Figure 21 (continued). Spectral signature and standard deviation of five common species (a) tube anemone (b) red sea cucumber (Parastichopus), (c) deeplet sea anemone, (d) squat lobster, and (e) the gorgonian Paramuricea Comparison of the mean spectra from four of these species (f). Note that the vertical scales in each graph are not the same – scale ranges have been used to best highlight each spectral signature. (Figure continues on next page)

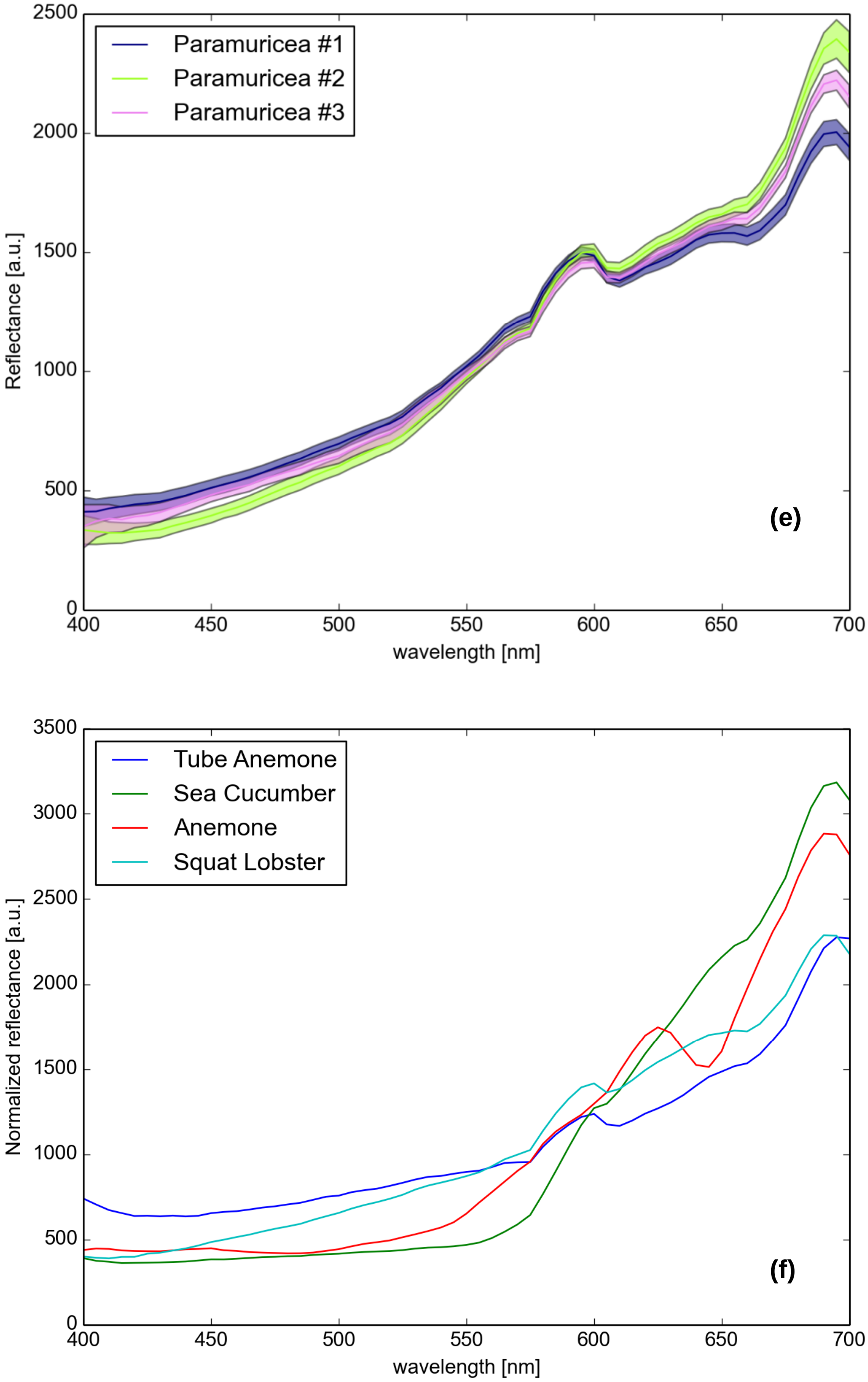


Figure 21 (continued). Spectral signature and standard deviation of five common species (a) tube anemone (b) red sea cucumber (Parastichopus), (c) deeplet sea anemone, (d) squat lobster, and (e) the gorgonian Paramuricea Comparison of the mean spectra from four of these species (f). Note that the vertical scales in each graph are not the same – scale ranges have been used to best highlight each spectral signature.

Distinctness of spectral classes varies considerably between classes and groups of classes. For example, if there are two distinct objects that appear green and where the colour is created by the same pigments, their spectral signature is less distinct than if one of the objects appear red, and contains other pigments. Nevertheless, the two green objects can be distinguished by detecting the different concentration ratios of the pigments using UHI data. When the results for this report were produced by Ecotone in 2015, measures for distinctness of spectral classes were not analyzed. However, tools have recently developed by Ecotone to give quantitative information about the uniqueness of the spectral classes in the library, and a confusion matrix could very well be produced from this type of analysis. Recently, Ecotone have demonstrated that the UHI can even uniquely identify and count salmon lice (Sæther et al. 2015, Aas et al. 2016).

The robustness of the selection method for the reference spectra can be improved from the methods used in 2015. Ecotone are currently working on a tool that will project the spectra into a lower dimensional space to identify outliers. Note, however, that the reference spectra are calculated by the mean of several pixels which will reduce the effect of these outliers. The spectral signature can then be used to classify thousands of pixels, and hundreds of objects of the same class. Examples of objects where many objects of the same class were classified include sea urchins and anemones in the fjords of Svalbard, as well as in the Trondheimsfjord. The success of OOI detection is also context dependent. For example, red objects in a grey image scene are going to be much easier to identify compared to other grey-ish objects. This is also why growth and sedimentation on objects is challenging. A measure of confidence could be added as an attribute to the features in the shapefile. This could be estimated by several means depending on the classification algorithm. For example, using the Spectral Angle Mapper, the confidence can be expressed as the spectral angle between the average spectrum of the pixels comprising the object and the corresponding reference spectrum. Further development of all these methods related to spectral analysis and classification is ongoing at Ecotone.

Figures 22-25 present some further examples comparing video data with the classified and spectrally enhanced images. The images illustrate the appearance of four common taxa (*Munida, Bolocera, Paramuricea,* and *Parastichopus*), and rust. In Figure 22a we barely see two closely occurring sessile colonies with indication of branches (the edges of the colonies are not smooth), but no confident species identification can be made. The UHI-RGB image (Figure 22b) provides a clearer picture, and the shape and colour indicates that these most likely represent two young colonies of the coral *Paramuricea placomus*. However, a closer inspection would be needed to confirm this suggestion.

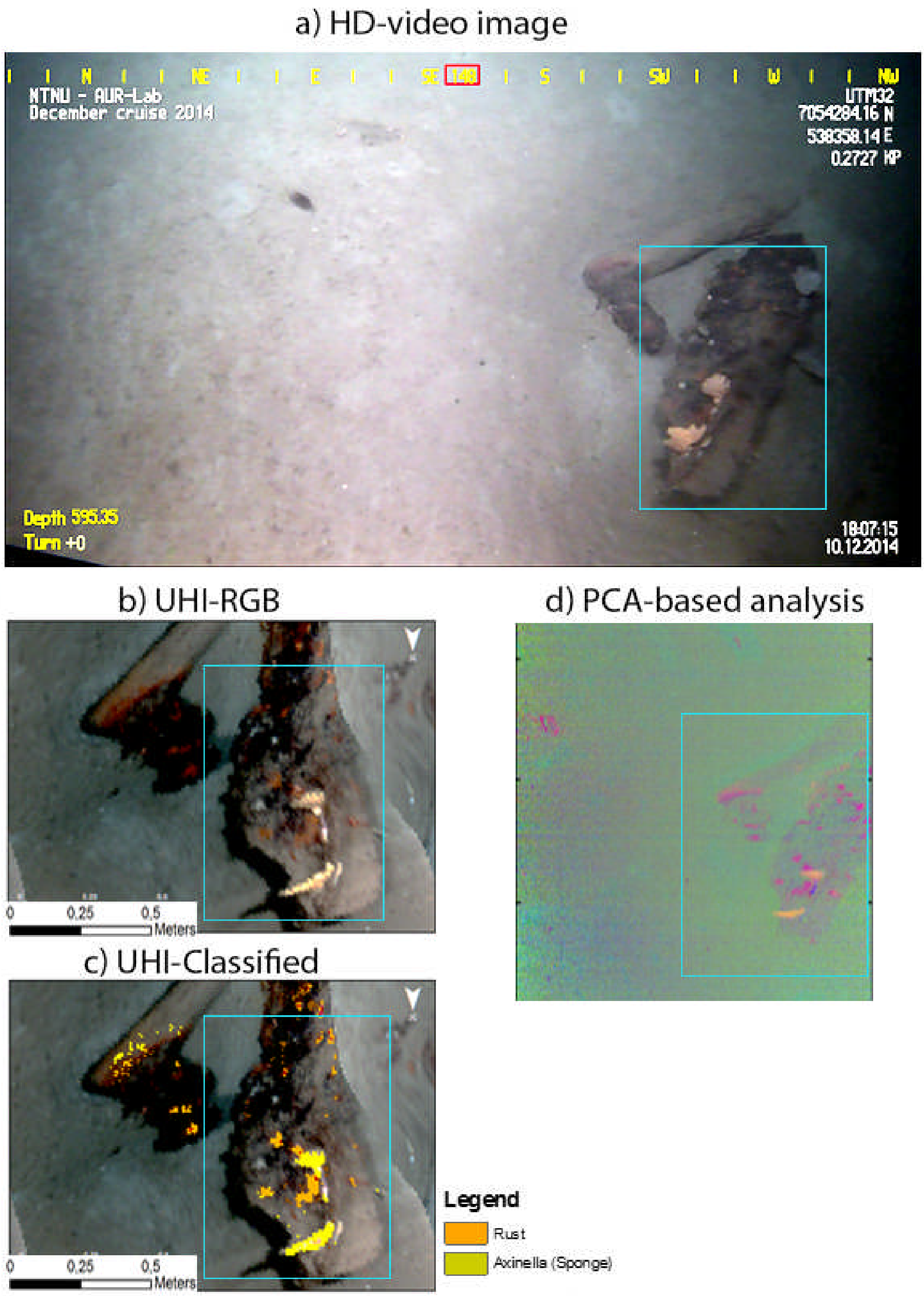


Figure 22. a) Video still showing yellow to orange sessile organisms growing on a manmade object, b) UHI-RGB image of the same organisms (seemingly a Paramuricea *coral) and the surrounding rust patches, c) UHI-RGB image with classification overlay, d) image from Ecotone's software using Principle Components Analysis (PCA) method (section 4.2) with three eigenvalues removed, highlighting the spectral separability of the OOI from the background.*

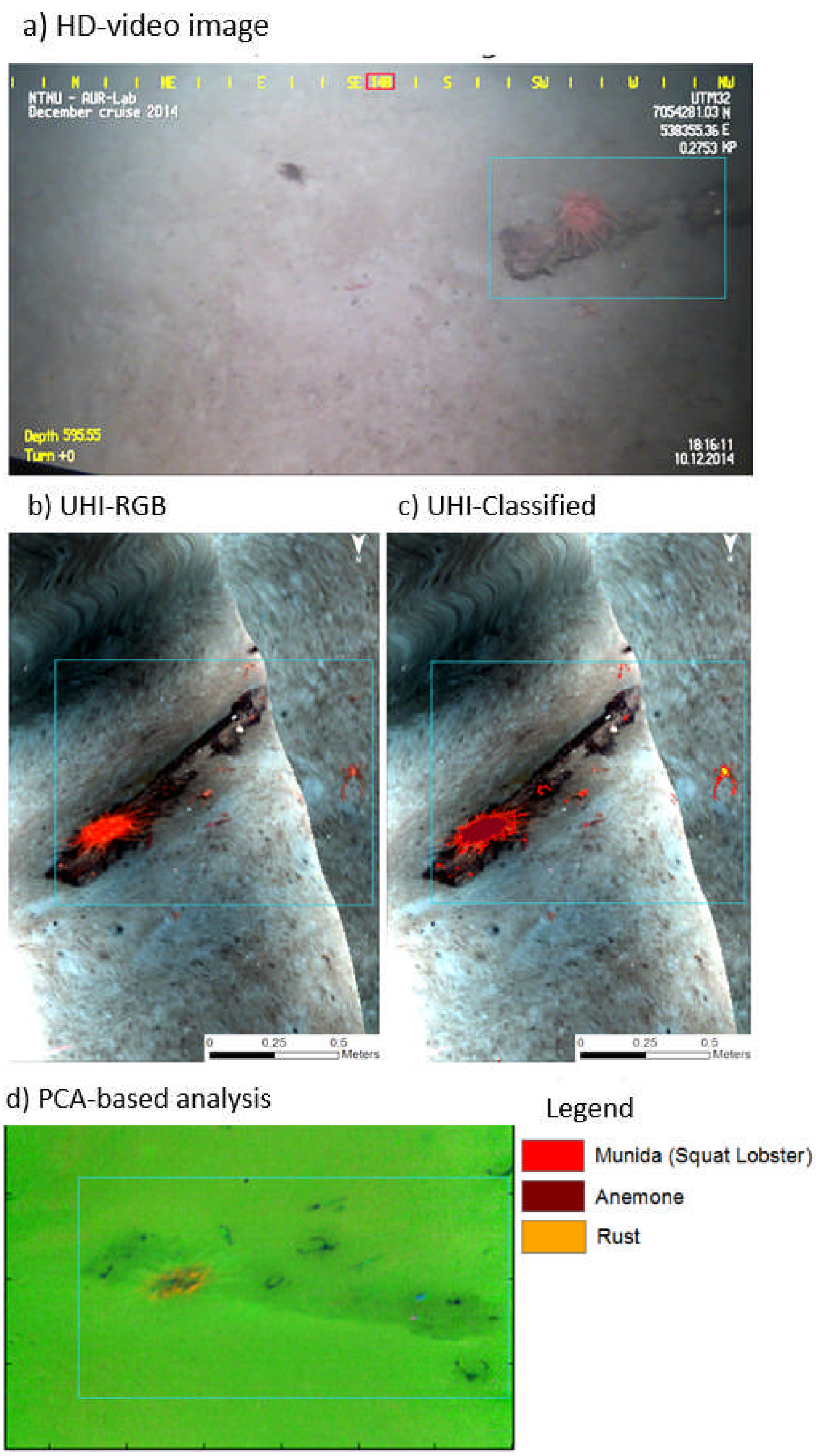


Figure 23. a) Video still showing an anemone (Bolocera sp.) sitting atop a manmade object, b) UHI-RGB image of the same anemone and surrounding squat lobsters, c) UHI-RGB image with classification overlay showing identification of sea anemone and squat lobster, with some class contamination on the Squat lobster (from class Rust) and on the tentacles of the anemone, d) image from Ecotone's software (PCA-based analysis) with two eigenvalues removed to show the number of lobsters present in the scene surrounding the anemone, despite not being clearly visible on video or UHI-RGB.

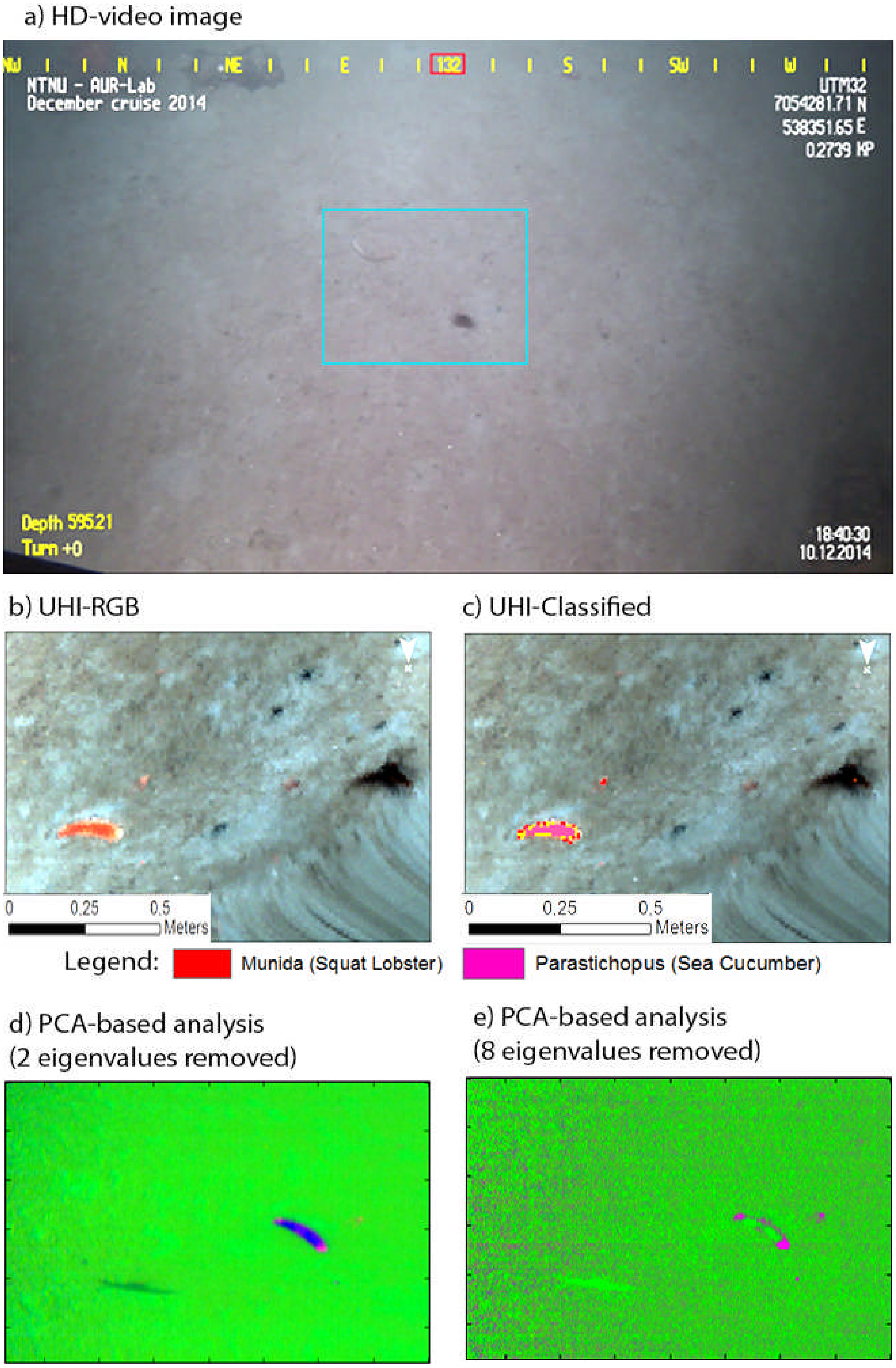


Figure 24. a) Video still of a sea cucumber, b) UHI-RGB of the same sea cucumber, c) UHI-RGB of the same sea cucumber with classification overlay. Notice the three pixels just above the sea cucumber representing the squat lobster class, d) UHI image (PCA-based analysis) with two eigenvalues removed highlighting the sea cucumber, e) UHI image with eight eigenvalues removed revealing the tiny squat lobster next to the sea cucumber.

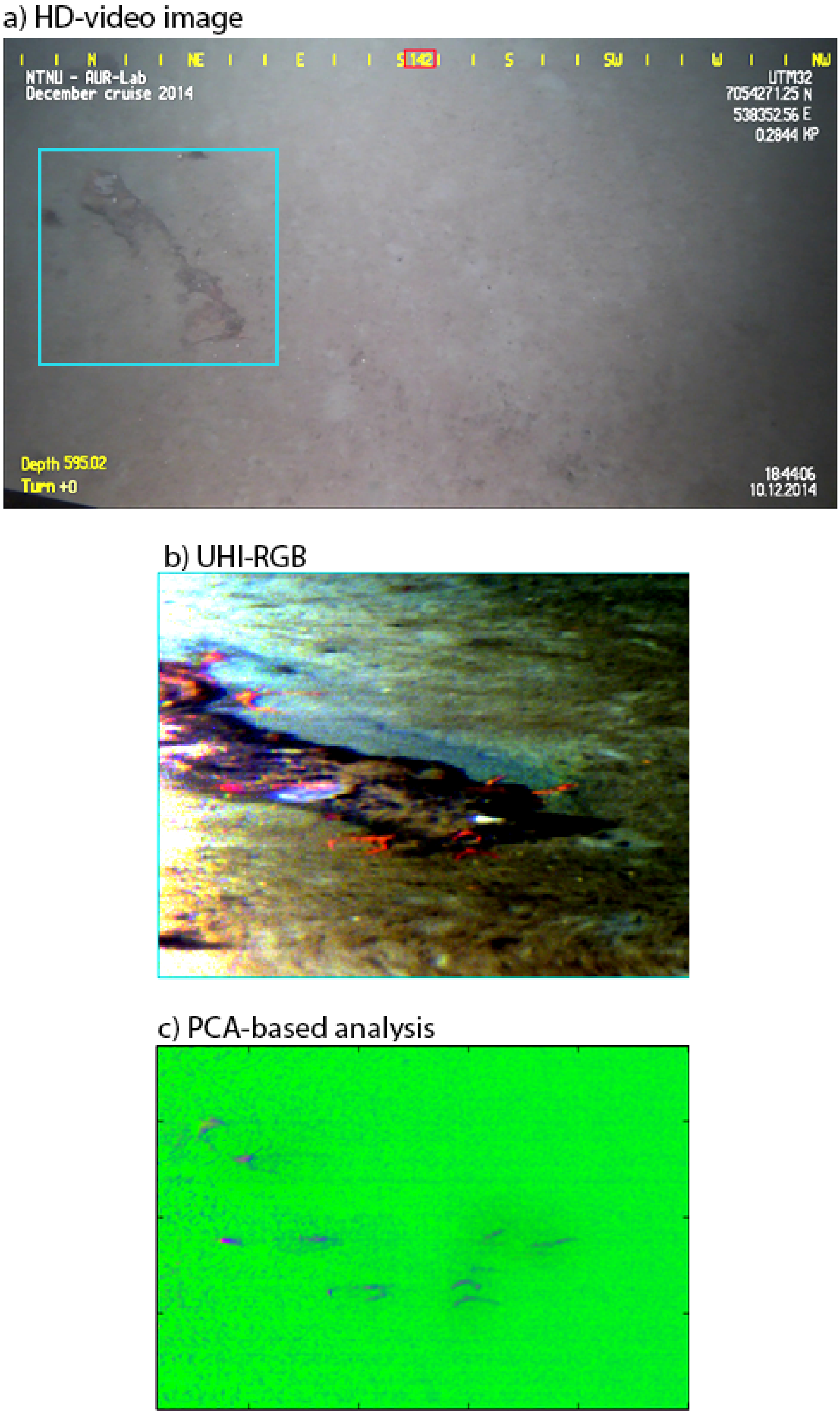


Figure 25. a) Video still of a manmade object b) UHI-RGB image showing at least nine squat lobsters on or around the object, c) image from Ecotone's software (PCA-based analysis) with three eigenvalues removed to highlight the squat lobsters d) image from Ecotone's software with three eigenvalues removed.

In Figure 23a we can see the deeplet anemone (*Bolocera tuediae*) living on manmade objects. The dark object to the left in the image appears to be a tube anemone (Cerianthidae Indet.). Since the overlap between the UHI image (b, c) and the video image (a) is not the same it is hard to compare the exact location of squat lobsters (Munida sp.). The tube anemone (Cerianthidae Indet) in (a) is not represented in the UHI image.

The presence of a sea cucumber (*Parastichopus tremulus*) is outlined in Figure 24 a. Next to the left corner there is a dark object most likely representing a tube anemone. This tube anemone also becomes more visible in the UHI images (b,c) but was not an object of interest for this processing example which focussed on detection of the sea cucumber and is detected in the enhanced UHI images (d,e) which also picks up the presence of the small squat lobster with further processing (e).

Figure 25 shows an example where squat lobsters which are very small features not detectable in video (a) with the angle and camera distance applied can be seen on the UHI-RGB (b) and enhanced UHI images (c).

The examples presented above illustrate how filtering of UHI images (removal of certain eigenvalues) can highlight selected taxa with a known and characteristic colour spectral composition. The comparison of visual detectability from video stills versus RGB-enhanced UHI images does not, however, represent a general objective comparison of image resolution and colour contrast. To enable such a comparison to be made, crucial parameters including camera angle and distance to object should have been similar. It is clear that a conventional HD-camera closer to the seabed, providing the same narrow field view as used for the UHI, would have provided sharper images with better colour saturation and contrast.

A more important issue to consider in the future is the potential benefits of implementing hyperspectral parameters in automated image analyses where other parameters (e.g. shape of objects and structure of patterns) are already used for automatic detection of selected species (Clement et al 2005; Di Gesu et al 2003; Gordan et al, 2006; Purser et al. 2009; 2013; York et al 2008).

5.4 Evaluation of UHI data for sediment mapping

Standard sediment grain size maps produced by MAREANO are based on multibeam bathymetry and backscatter data, using visual and physical sampling for ground truthing of the acoustic data (see also Thorsnes et al. (2015). Other sediment maps produced by MAREANO include the sedimentary environment map, indicating areas of sediment erosion or deposition, and the sediment genesis map which provides information on the geological origin of the sediments at a particular location. For the purposes of this project UHI data are considered in the context of their value primarily for sediment grain size mapping, although other sediment properties are also discussed here and in section 6.3.

Based on the current dataset and analysis results UHI data appear to offer no new information to complement or supplement video data which is of direct value for MAREANO sediment (grain size) mapping at the standard 1:100 000 scale. The spatial scale of UHI information is a poor match with the multibeam acoustic data (bathymetry and backscatter) which is the core dataset for sediment interpretation (Figures 26-28). Note that the zoom levels in Figures 26-27 and particularly Figure 28 far exceed the level of detail that a geologist interpreting 1:100 000 sediment distribution would use. These figures therefore illustrate the mismatch between UHI and multibeam data resolutions in the context of mapping scales required for MAREANO. At present UHI data classification is not able to distinguish between sediments of different grain sizes or origins which is what MAREANO is required to map, further UHI classification does not currently detect disturbed sediments e.g. burrows which are often an important input to geological interpretation.

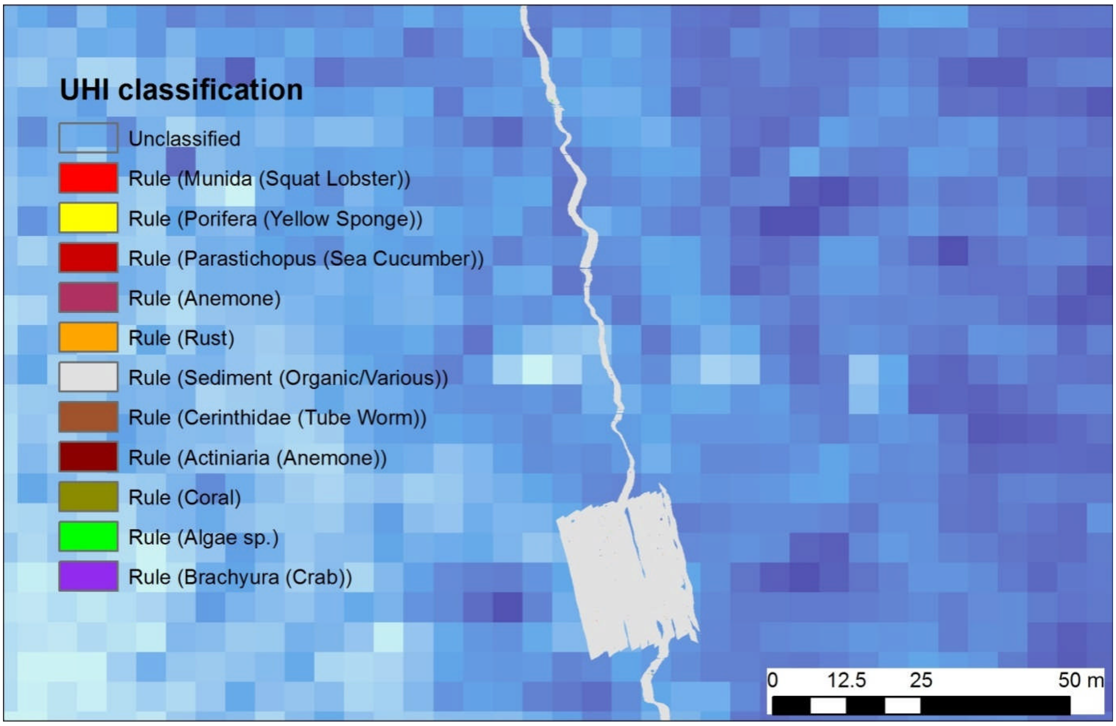


Figure 26. UHI classification with 5 m resolution multibeam (blue pixels). Classified sediment is shown in grey, but no other details of the classification given in the legend are visible at this 1:1000 map scale. This map scale (1:1000) far exceeds the detail that a geologist interpreting 1:100 000 sediment distribution would use.

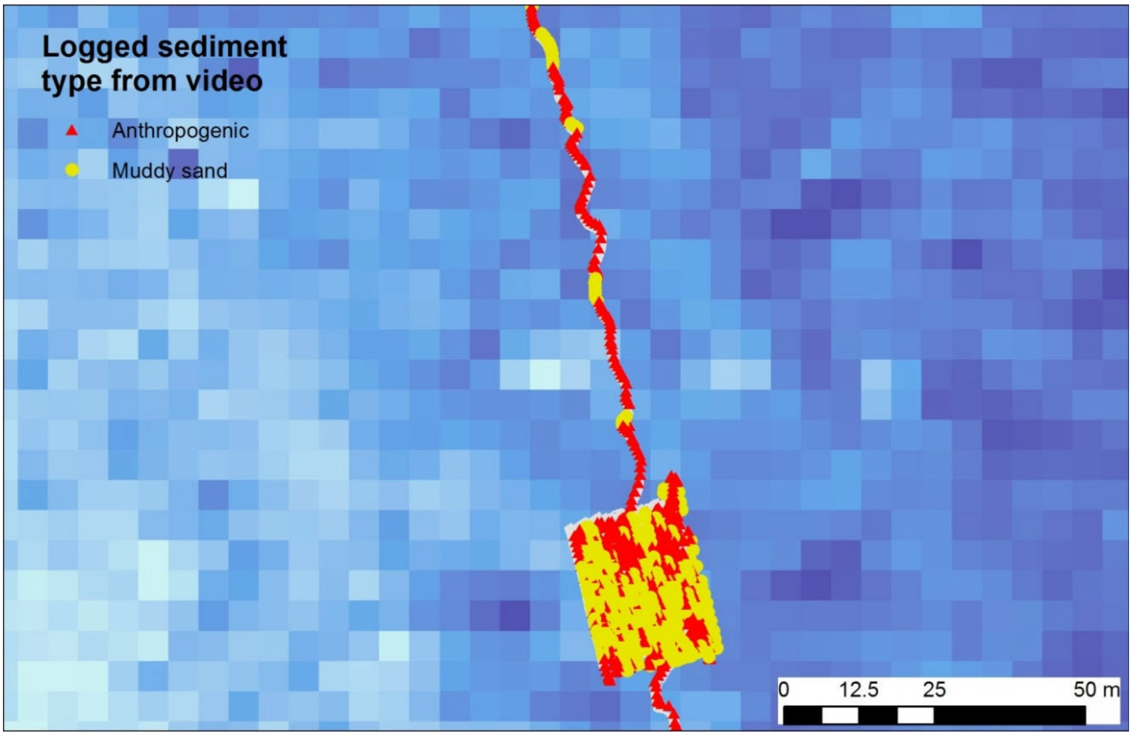


Figure 27. 5 m multibeam resolution (blue pixels) and geo-logged shapefile showing bottom type. Note that muddy sand is the dominant sediment type throughout the area but anthropogenic objects have been logged where present. This map scale (1:1000) far exceeds the detail that a geologist interpreting 1:100 000 sediment distribution would use.

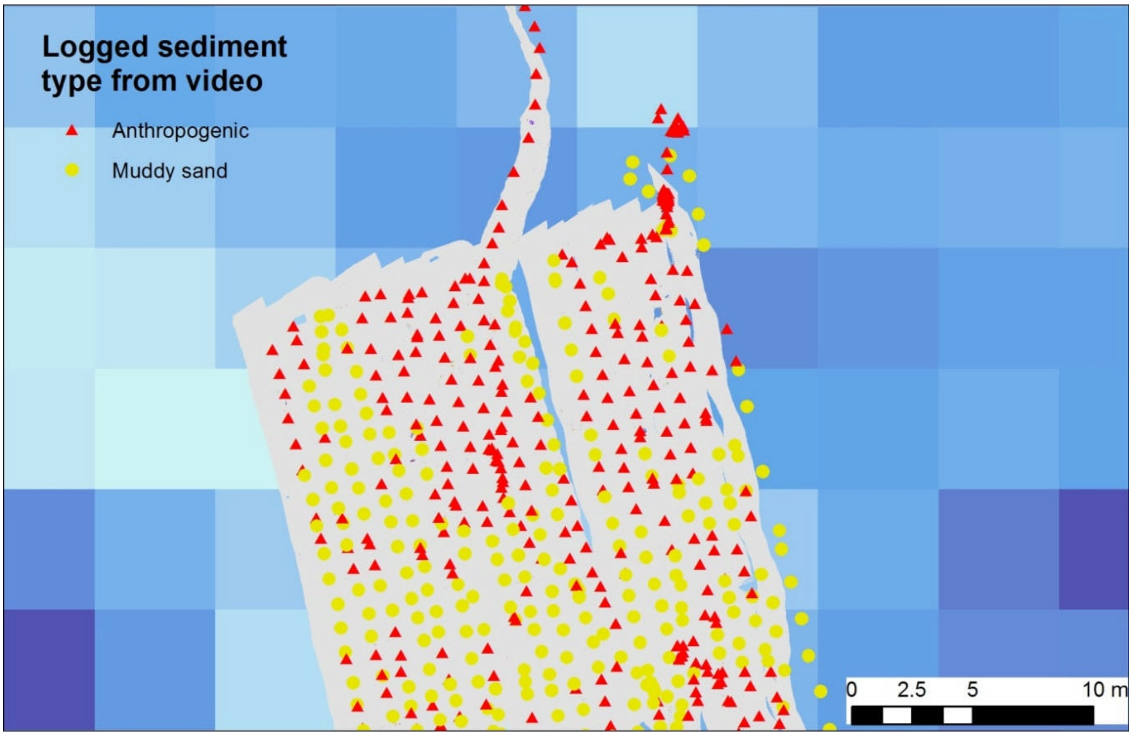


Figure 28. 1:250 view of 5 m multibeam resolution (blue pixels) and geo-logged shapefile showing bottom type overlain on UHI classification. Note that geo positions are 1.5 m ahead of the centre position of the ROV, estimating the field of view of the video camera. The UHI data are directly below the ROV.

Detailed examination of the data reveals several instances of uncertain positioning and artefacts in the RGB images which make the data difficult to use for geological (and biological) interpretation. Some examples are shown in Figures 29-36 from the central part of the box, where the disparities are easier to recognise, however these uncertainties persist throughout the dataset, also between adjacent lines on the box survey.

Although supposedly imaging the same area of seabed, the results from UHI data from Line 2 and the box survey are very different. UHI data from the box survey show bare sediment with no detectable biological OOIs (Figures 29-30). Line 2 data from the same location show the presence of a rock and associated benthic fauna (Figures 31-32). The benthic organisms are captured by the biological based UHI classification of data from this line (Figures 32, 34). Zooming in further on the central part of this area we see the details captured in the RGB and classified UHI data from the Line 2 survey (Figures 33-34). Zooming on the same area using the data from the box survey, however, reveal no classified OOIs (Figure 35) and examination of the corresponding RGB image shows that no OOIs have been detected and further that the RGB image suffers from motion artefacts (though it is clear that the seabed is not the same seabed as imaged in Figure 33).

This lack of spatial consistency between overlapping surveys is a concern for any further use of the data in seabed classification. It is beneficial that the overlapping lines of the box survey and the separate Line 2 survey has given us the opportunity to examine these problems, which may not have been detected had a single, line survey been conducted. We [MAREANO] are uncertain if the lack of consistency is due to improper geocorrection of the UHI image data or errors in the ROV positioning/timing. It may be possible that the fine scale details we are observing in these images are within the error limit of the underwater positioning system used, this should be less than 10 cm but the scale of UHI data operates quite close to this limit. Whatever the cause, correction of positioning inconsistencies should be a priority for any future UHI surveys. Uncertain navigation does not necessarily make the data unusable for geological (or biological interpretation), especially if the data will be interpreted/analysed together with coarser resolution acoustic data, and/or for broader scale mapping purposes, however it is essential that the data user is made aware of the limits of navigation uncertainty, so they can consider any analysis/interpretation of the data in an appropriate manner.

As we see from Figures 29 and 36 in particular , the RGB images are not of sufficiently good (consistent) quality for boundaries between sediment types to be directly determined. This means that visual determination of sediment type from video remains a more useful tool for MAREANO at the present time. No spectral libraries of sediment type are currently available that would allow fuller use of the UHI data to characterise the sediments in terms of grain size or other properties. To provide the necessary data to prove any link between UHI data and sediment properties in the field and start building up a library for practical use, considerable further work is required. UHI data would need to be analysed together with known physical samples and/or very high resolution visual observations that are able to conclusively determine the grain size and other properties.

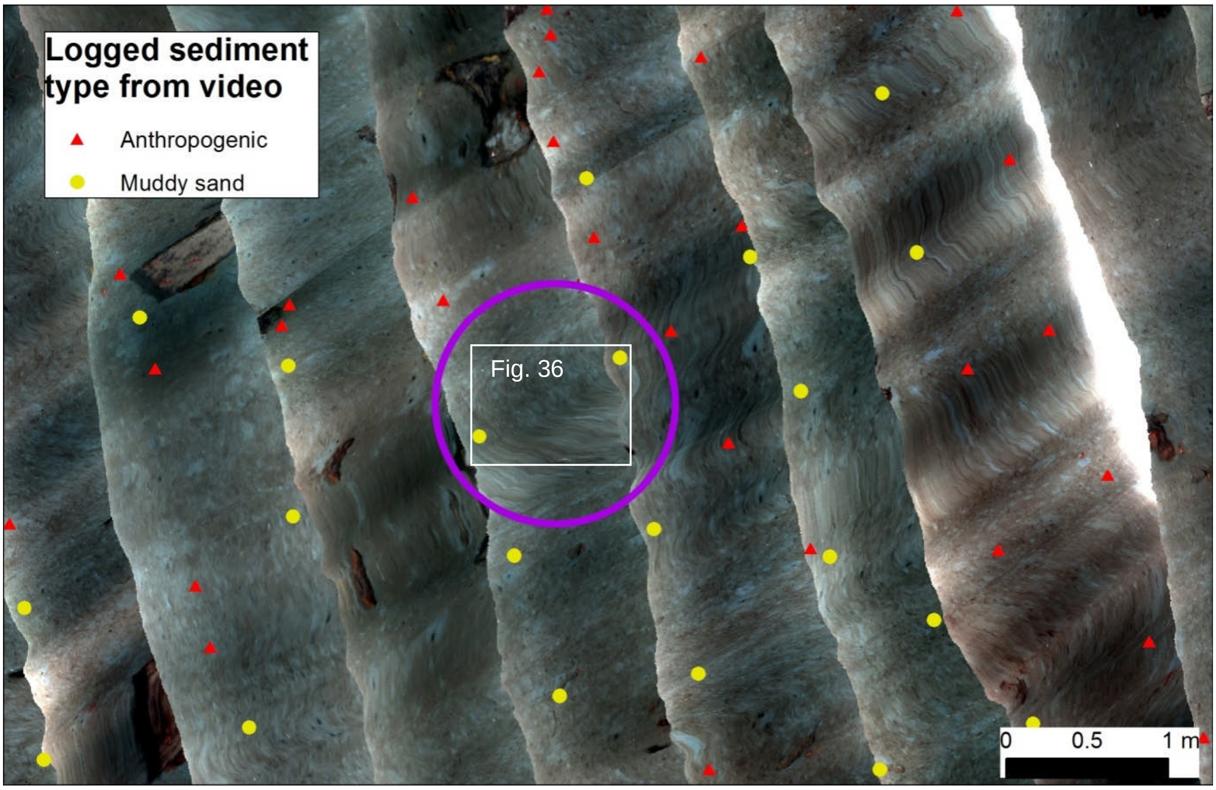


Figure 29. RGB images from box survey (map scale 1:40). Note also the 'swirly' sections of several RGB images where the UHI data appears stretched due to unstable ROV movements. Purple circle indicates the area with a mismatch in the objects observed between lines and is common to Figures 29-32.

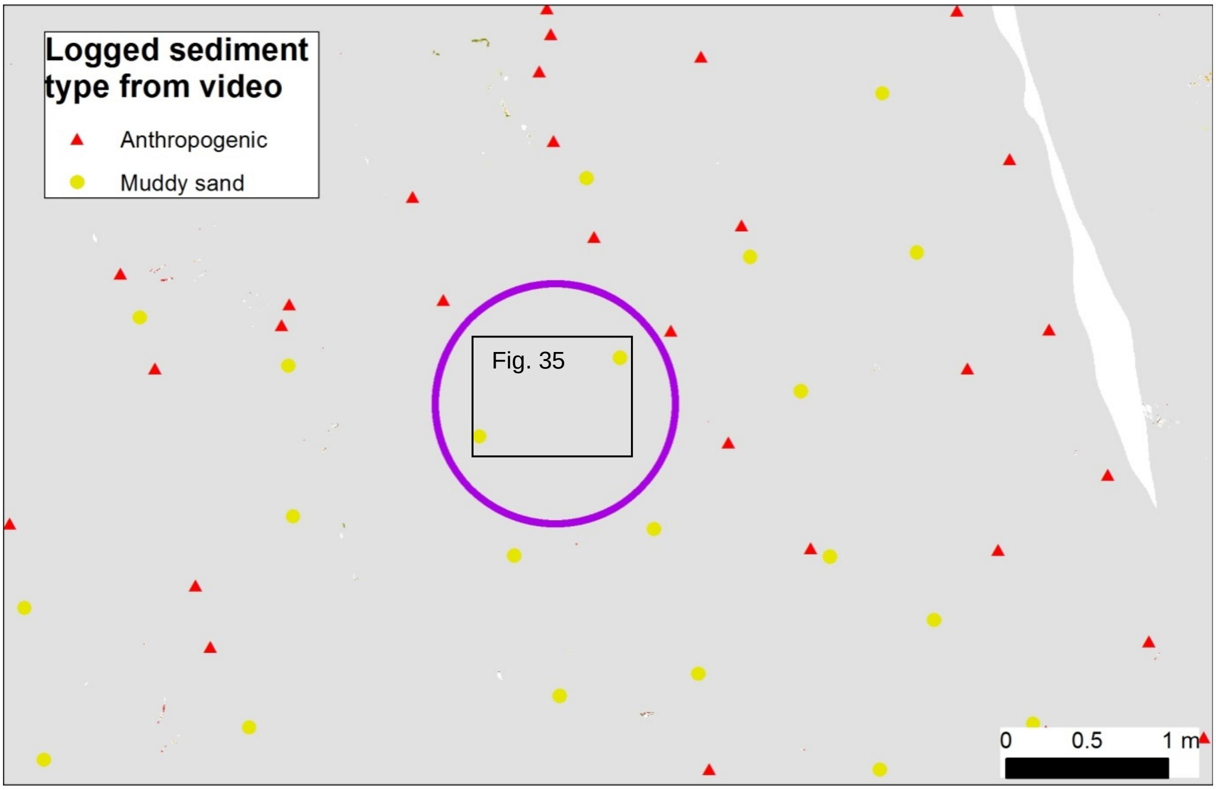


Figure 30. Classified UHI from box only (1:40) for the same area.

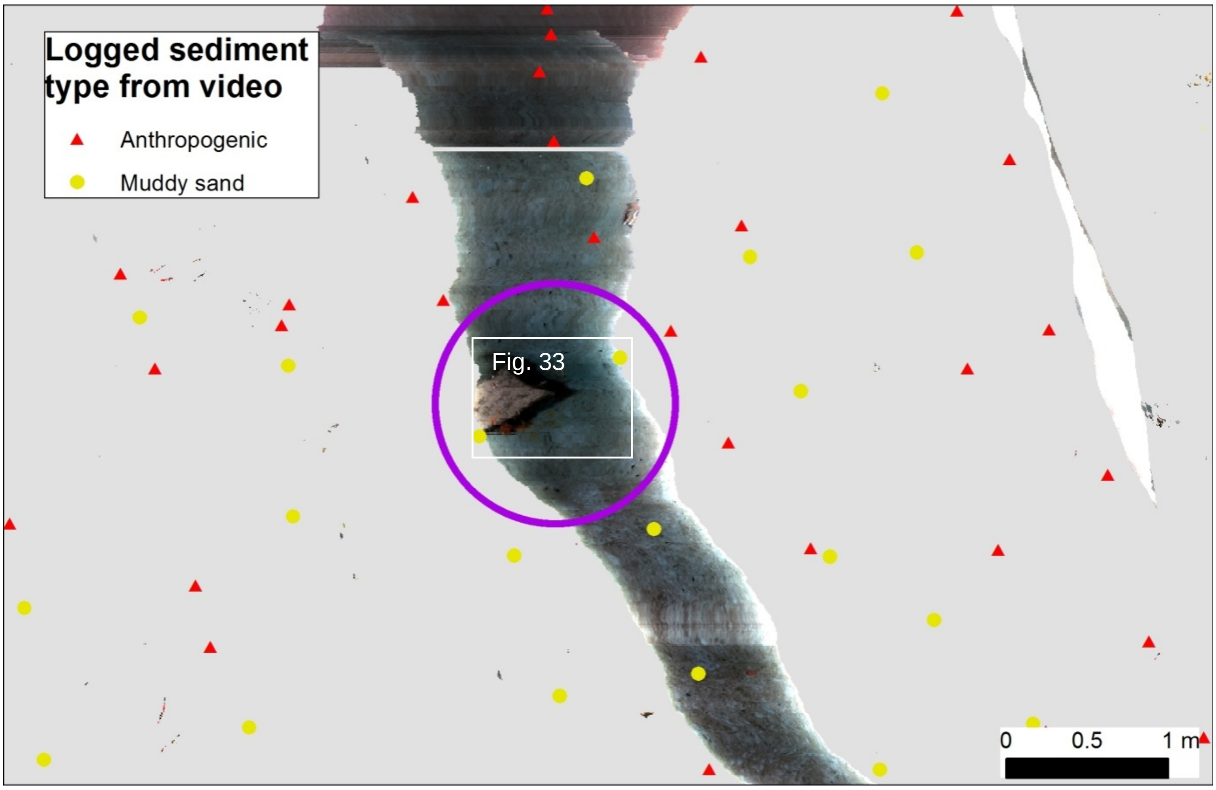


Figure 31. RGB data from Line 2 overlain on classified UHI from box area (1:40).

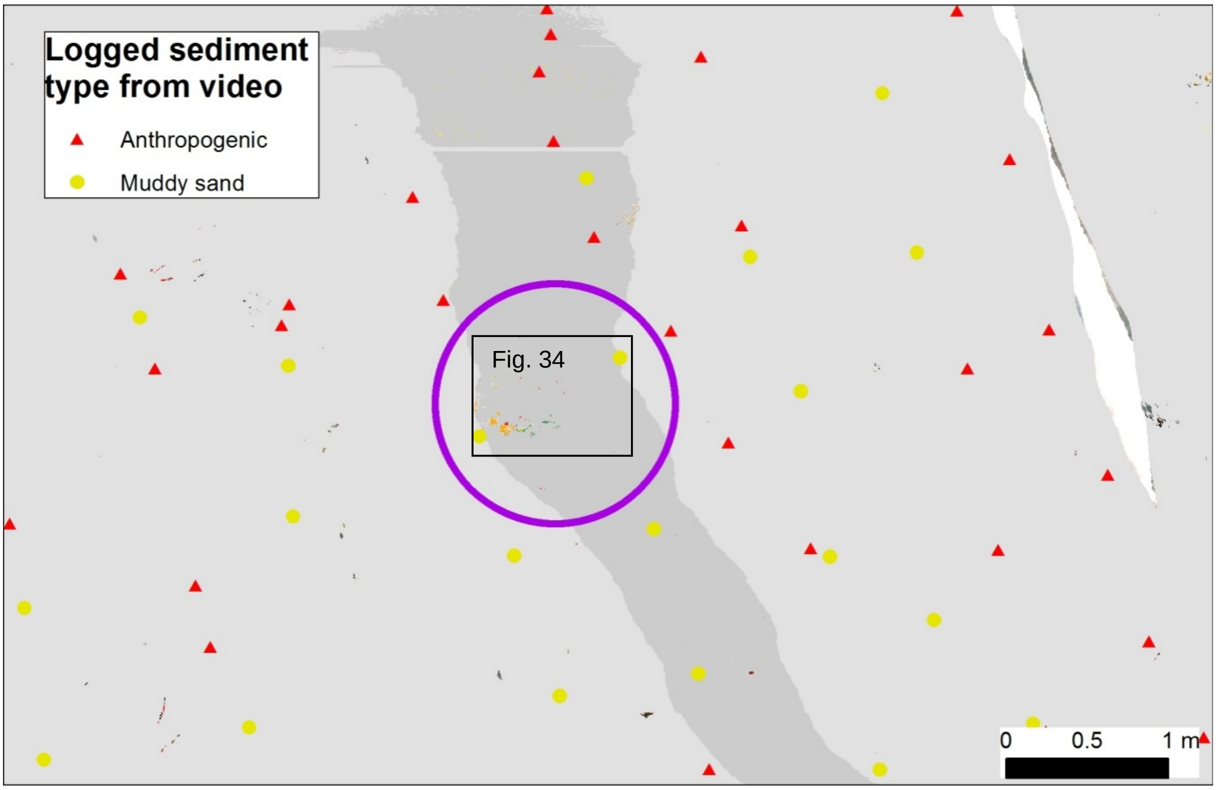


Figure 32. Classified UHI from box survey overlain by classified UHI from Line 2 (1:40). The sediment class from line 2 is shown in a darker grey to distinguish the classification from this line from that from the box.

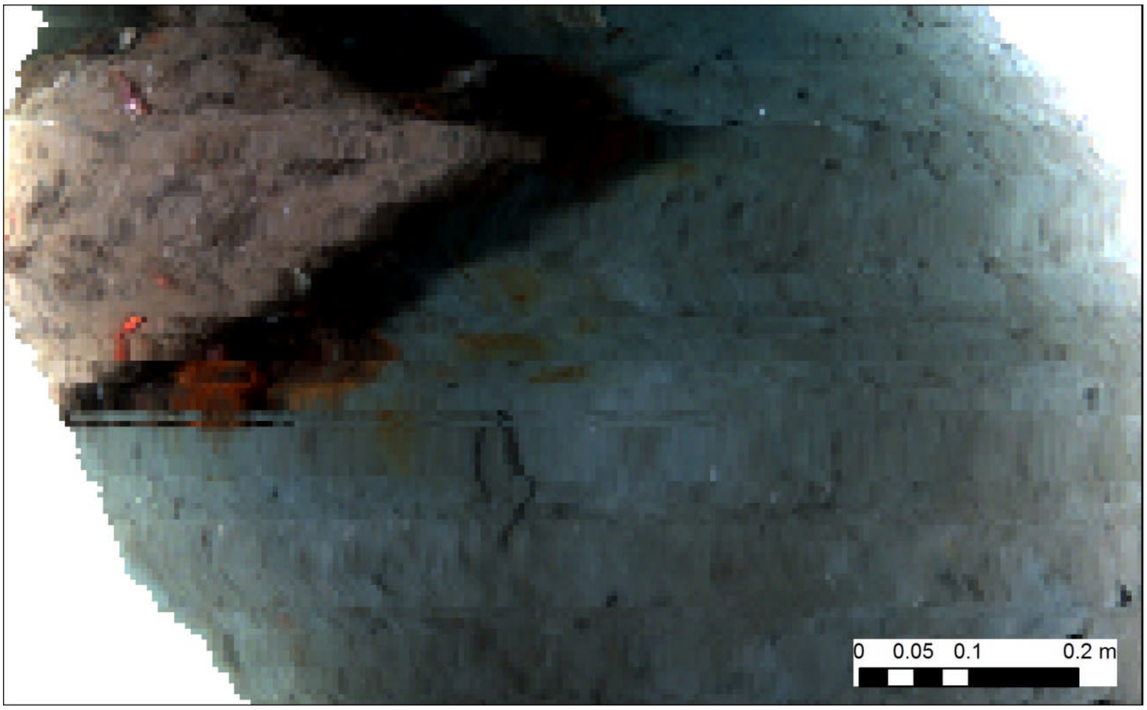


Figure 33. Zoom on UHI-RGB image from Line 2 inside the purple circle. Map scale 1:5

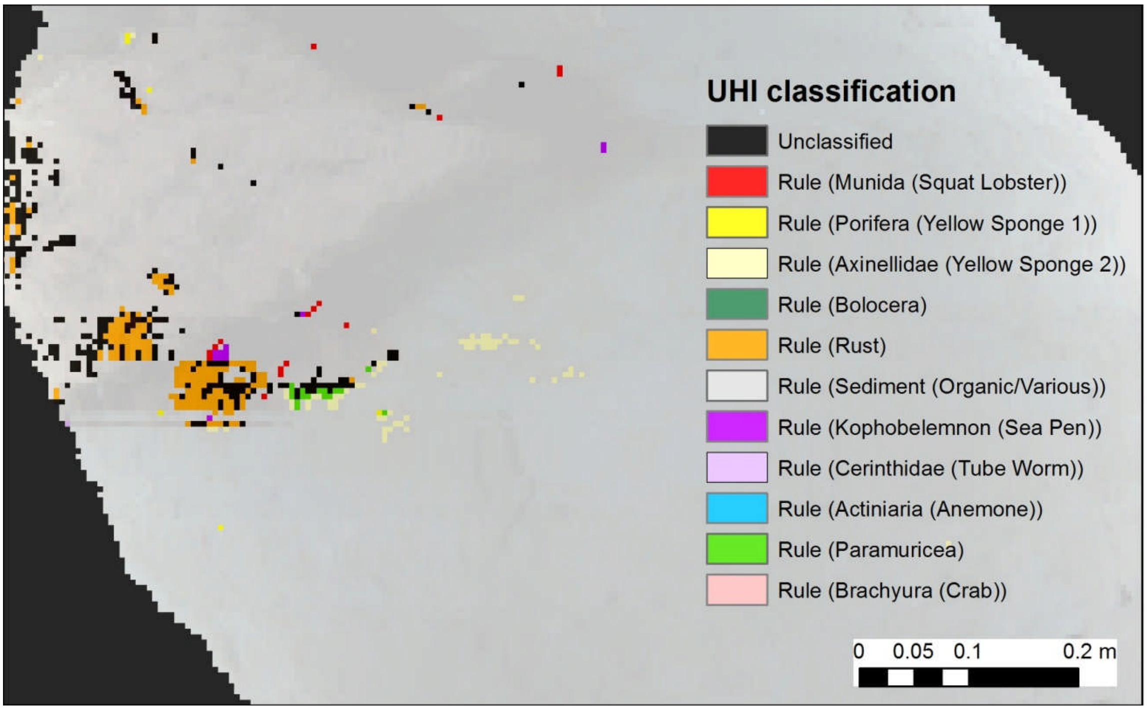


Figure 34. Zoom on UHI classified image from Line 2 inside the purple circle. The classified image is shown as a semitransparent layer over the RGB image (Figure 33). Map scale 1:5. Note the classification is for biological objects and rust only and does not distinguish between sediment types. The majority of bare sediment falls under the 'Sediment' class.

Figure 35. Zoom on UHI classified image from Box survey inside the purple circle i.e. exact same area as Figure 34 above. Map scale 1:5. No OOIs are detected by the classification and the whole area is classified as sediment only.

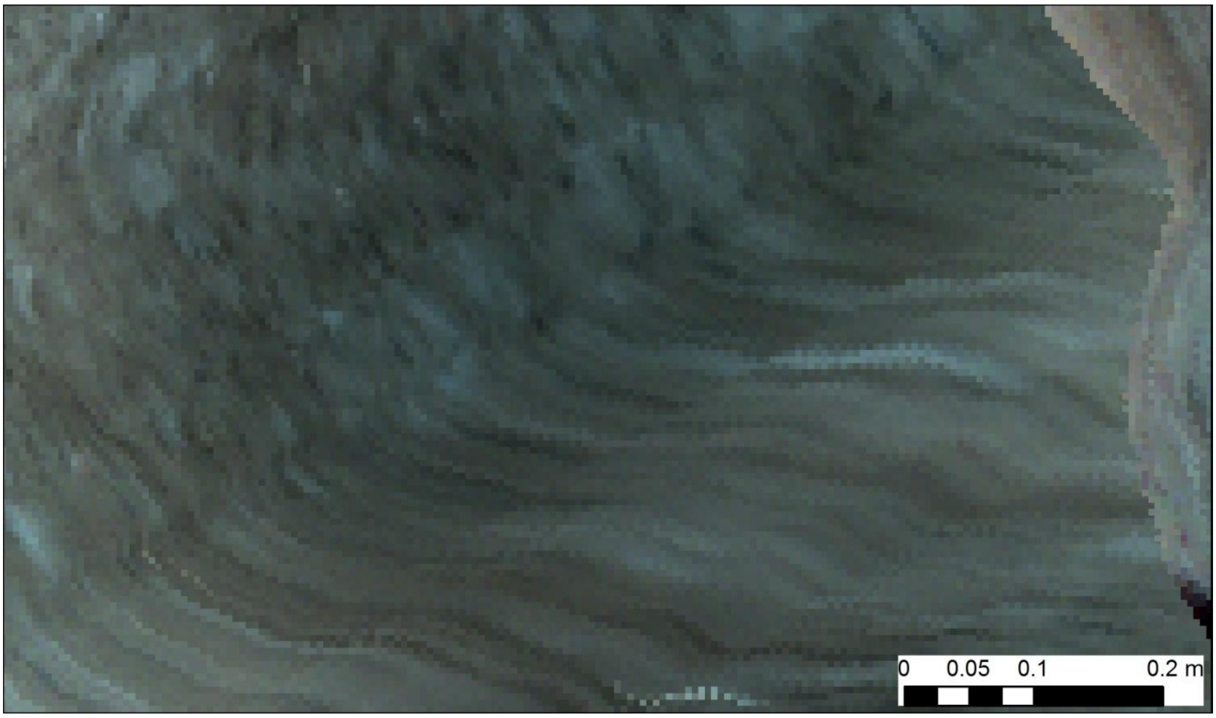


Figure 36. Zoom on UHI-RGB image from Box survey inside the purple circle i.e. exact same area as Figure 33 above. Map scale 1:5. This shows the RGB version of the data used to produce the classification of data in Figure 35 above, and explains why no classification results are obtained. The swirly nature of the image is a result of ROV movements that cannot be corrected for with available time/position information.

No classified maps have been provided by Ecotone that attempt to distinguish between different sediment types, instead the analyses have focussed on biological, and artificial objects of interest with bare sediment (of all types) being represented by the ‘unclassified’ class (section 5.3). Nevertheless, following workshops with MAREANO where the potential use of the data for sediment characterisation were discussed, Ecotone have produced some results which indicate promise and considerable scope for development of use of UHI data for sediment classification in the future. As part of a preliminary investigation of the potential use of UHI data for sediment mapping, UHI data from four selected areas of interest (AOIs) including different signatures in HISAS 1030 data (Figures 37, 38) were examined.

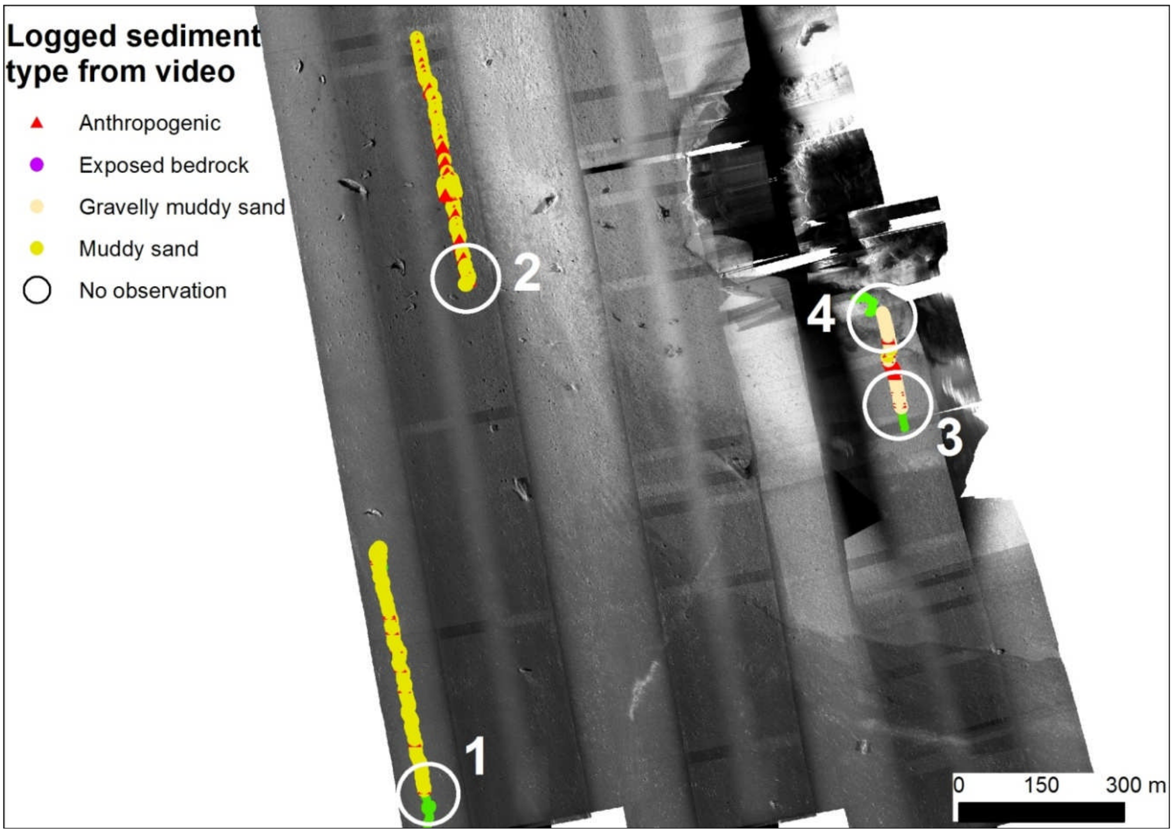


Figure 37. General location of AOIs for sediment evaluation, shown overlain on HISAS 1030 data (33 x 33 cm resolution). Note that green lines are ROV survey lines where no position information is available for logged video observations. These generally correspond to areas where no or poor UHI data were acquired due to ROV manoeuvring. This includes the area to the north of AOI 4 (shown in green only) contains gravelly muddy sand and exposed bedrock. This contrasting bottom type can also be seen in Figure 38.

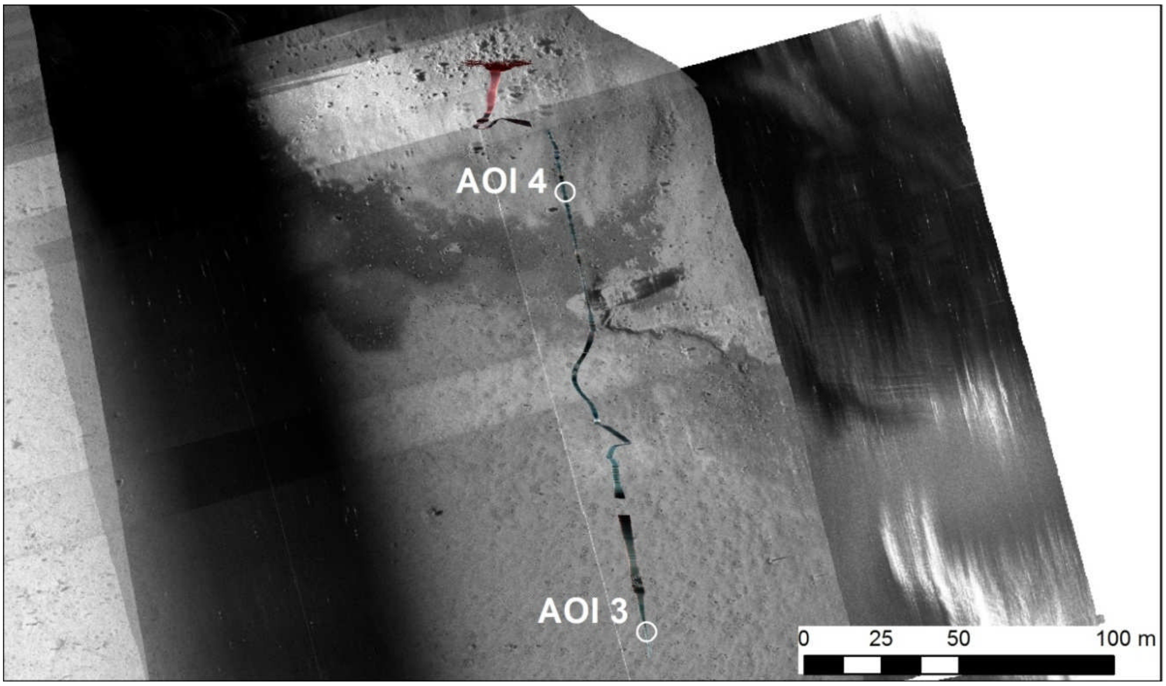


Figure 38. UHI-RGB data from Line 3 showing the precise location of AOI 3 and 4 on line 3 in relation to HISAS 1030 data.

For each AOI 200 x 200 pixel sub-images were extracted from the original UHI images. We can see from the RGB images that AOI 3 has a much higher reflectance in the RGB images (Figure 39) and this can be verified by comparing the reflectance spectra for AOIs 1-3. Upon visual inspection the reflectance spectra look very similar (Figure 40) but by applying selective principle components analysis (SPCA) the components in the spectra representing the large degree of similarity can be subtracted, giving the reduced reference spectra where the differences are much more apparent (Figure 41). Similar spectra in this context refer to the average spectral signature from each 200 x 200 pixel AOI.

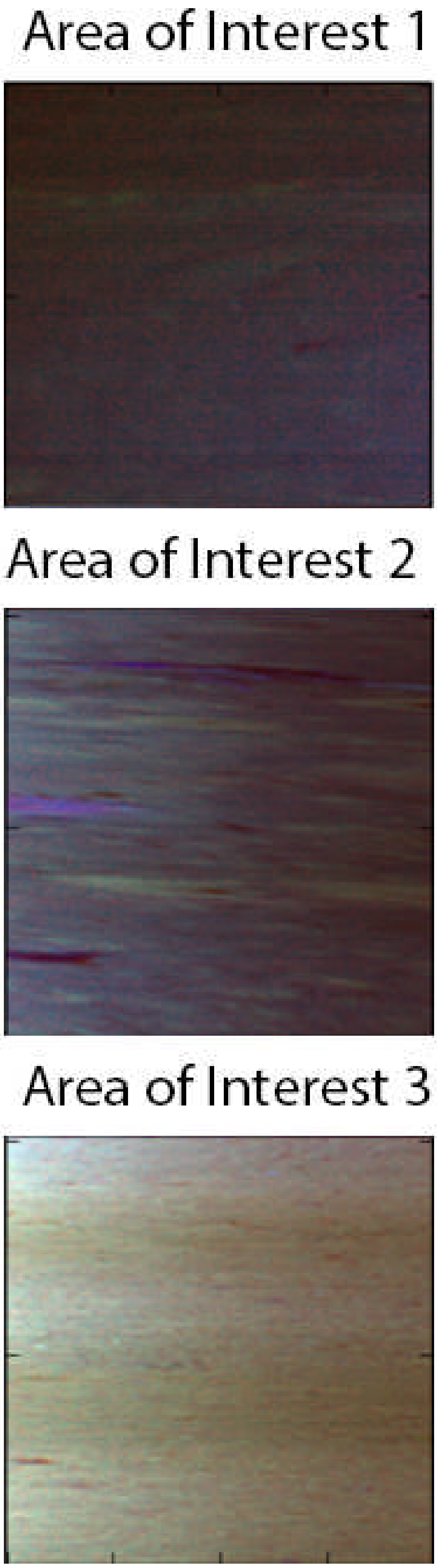


Figure 39. RGB images showing AOI 1-3, respectively, from the top. The subsamples are approximately 20 cm across.

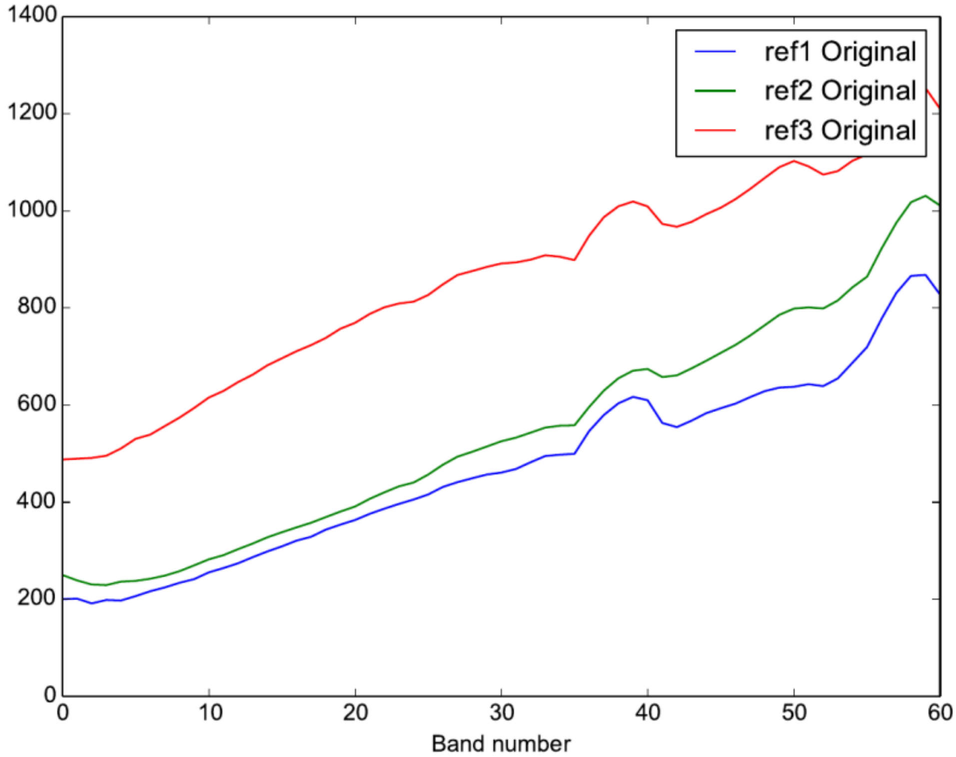


Figure 40. Reference reflectance spectra from AOI 1-3, shows that the shape of the spectra from the three areas looks similar. Most of the similarity can be explained by the first Principal Component.

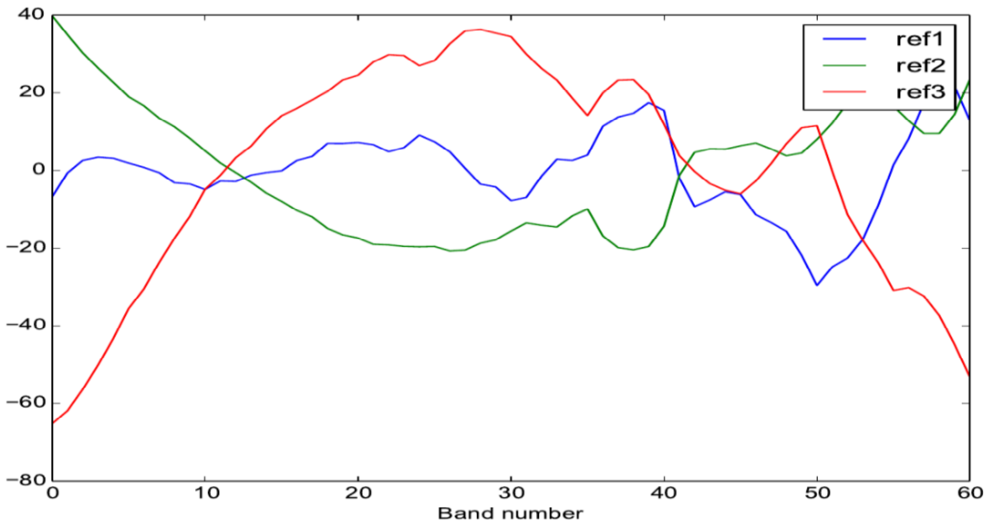


Figure 41. The reference reflectance spectra from AOI 1-3 reduced by SPCA. The spectral differences shown here are explained by the remaining Principal Components.

By calculating the correlation coefficient between the reference spectrum and every pixel in the UHI images a measure of spectral separability can be obtained. Figure 42 shows the correlation coefficient between the reference spectra from AOIs 1 – 3 and the sub-images from each AOI. The RGB images from each AOI are included to the left for reference. The correlation matrix is similar to a confusion matrix, commonly used to compare actual and predicted classifications, and employed by MAREANO in biotope mapping (section 5.5). Reference Spectrum AOI1 correctly shows a high correlation (close to 1) with the UHI pixel information from AOI1, but that the spectrum is weakly (close to 0) or negatively correlated (<0) with the pixels from the other areas. Reference Spectra AOI 2 and 3 also show a low or negative correlation with the other sub-images. The fact that reference spectra from each AOI are strongly correlated with pixel information from their respective sub-areas, but have weak or partial correlations with other sub-areas indicates good discrimination between sediment types, although further verification over more samples would be required for statistical validation. An example of this discriminatory ability is the lighter spots visible in the RGB image for AOI 2, which show a strong correlation with Reference Spectrum AOI3, and are distinct from the surrounding sediment in AOI 2. These patches of brighter sediment are often found in association with the biofilm layer on the sediment, and are usually a result of a disturbance (e.g., a burrowing animal depositing fresh sediment, or other movement by benthic organisms).

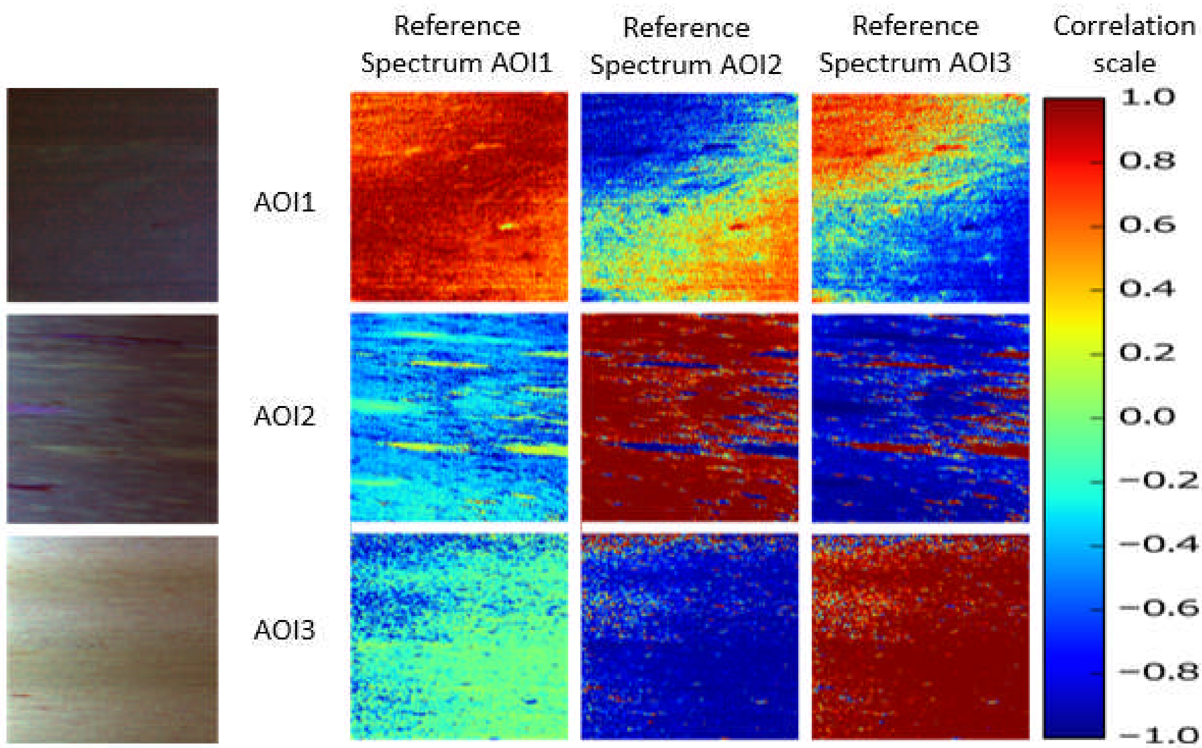


Figure 42. Colour maps showing the correlation coefficient between AOI 1-3, using a Reference Spectrum from each AOI as a basis for each comparison. Each subsample AOI 1-3 consists of 200 x 200 pixels, representing approximately 20 x 20 cm ground cover.

Another way of visualizing the UHI discrimination is to plot every sample (pixel) in a scatter plot, where the X and Y-axes are projections along two selected spectral components from Principal Components Analysis (PCA). Figure 43 shows an example where 200 random samples have been taken from each AOI. In this two-dimensional plane the samples from each AOI show a high degree of clustering and therefore give a parallel indication of the ability of UHI to discriminate between AOIs 1-3.

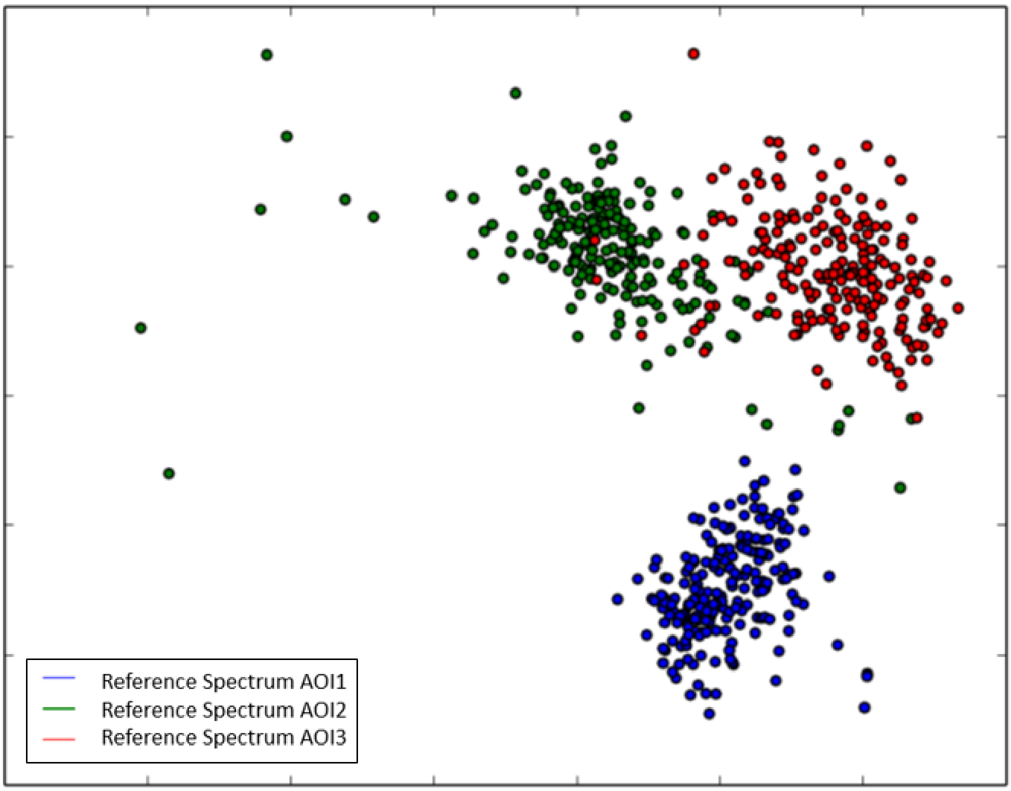


Figure 43. Scatter plot of 200 random samples from the three AOIs projected along two spectral components. The grouping of the pixels confirms the spectral separability between the three areas. If PCA had not been applied this figure would show almost completely overlapping points.

In general, reference spectra of known OOIs are necessary to perform a good (supervised) classification. If a reflectance library of sediment types were available, a full classification with a probabilistic measure for the coverage/mixing ratio of sediment types would be feasible. As no such library for underwater characterization yet exists, following on from this study Ecotone can start building the library sample by sample. Methods can also be applied to make an automatic (unsupervised) classification. One method for splitting data into clusters with similar properties is the k-means algorithm. Using k-means, a reference library can be made based on the Euclidean distance of components in the spectrum. User-specified limits are employed to constrain the classification, with the result that newly-added classes are created should objects not fall into any of the existing ones.

Figure 44 shows the results using k-means to identify classes across AOI 1-4. The unsupervised classification first groups the pixels into four classes using k-means classification, and adds new classes for pixels that do not fit into any of the initial categories (total of seven). AOI 1 and 3 appears to have mostly homogeneous sediment composition, based on the proportion of pixel classification. A few other clusters are visible in AOI 1, as well as the gradient between two similar classes, which most likely are due to uncorrected lighting differences (largest influence is the power surge from the ROV). AOI 2 and 4 have more heterogeneous compositions, with what appear to be shells and pockets of sand in between the undisturbed sediment.

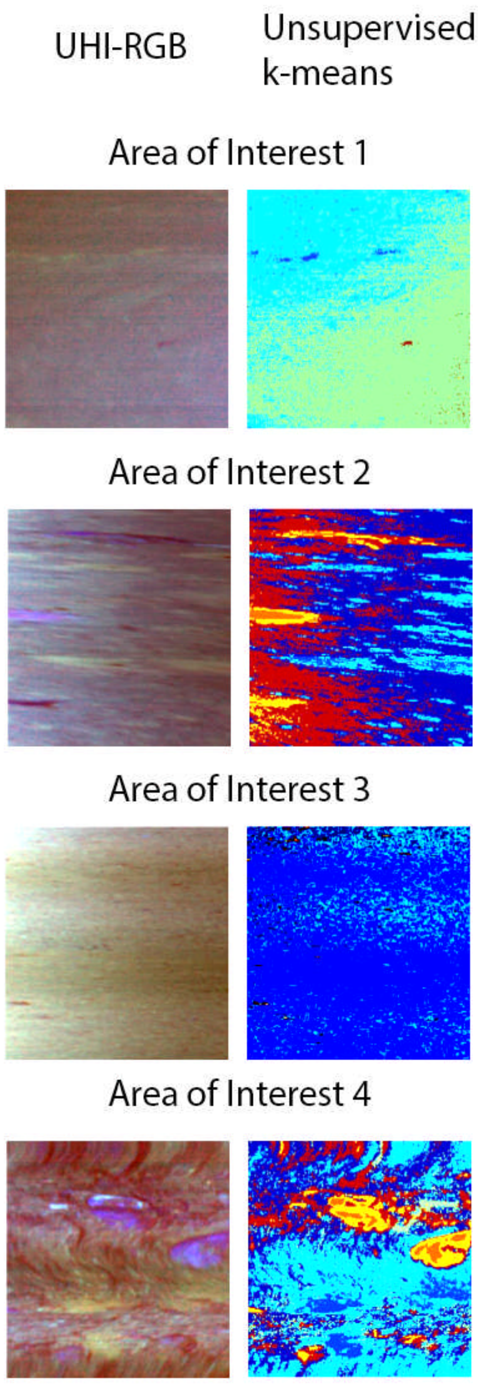


Figure 44. a) RGB images of AOI 1-4. b) k-means classification of AOI 1-4. Spectrally similar pixels are grouped together based on the Euclidian distance between the spectral signatures. A total of 7 classes were identified based on the input data, and at this point these represent clusters of pixels with spectral similarity and not a physical, classified object.

The k-means method tells us that there is a substantial difference in the spectra of these clusters. In order to assign a meaningful physical category to a specific object, further ground verification through sampling and several spectral measurements must be acquired in a controlled manner. This figure merely demonstrates the ability to use the UHI data to perform an unsupervised classification based on the spectral characteristics of selected areas on the seafloor.

These preliminary results of sediment discrimination from UHI are promising, but it should be noted that these results are a first ever test of field-UHI for sediment mapping and require significantly more validation, not least in conjunction with rigorous sampling which will allow a library of sediment types to be built up and tested. It will also be advantageous to compare the sediment properties detectable by UHI and acoustic data. We note also that biofilm was present at several of the test locations. It is unclear at this stage what the influence of this biofilm may be on any classification results and this needs to be investigated further. Certain geo-positioning will also be essential for any of these follow up studies.
The laboratory results obtained by Aarrestad 2014 also suggest there is useful sediment information that may be captured using UHI. A full evaluation of how field acquired UHI data compares with data obtained by traditional methods (acoustic, visual, samples) would be required to assess the added value of UHI data. Such an assessment is beyond the scope of this study and would require access to more comprehensive ground-truth information as well as data from a range of sediment types to support the field-acquired UHI data.
Aarrestad's (2014) results suggested that one area where UHI data may be useful is for indicating calcium carbonate content of sediments (Figure 45). Her results indicated that under laboratory conditions it is possible to detect the increase in reflectance with increase carbonate content for submerged sediments. Whether this detectability remains strong enough under field conditions, remains to be tested.

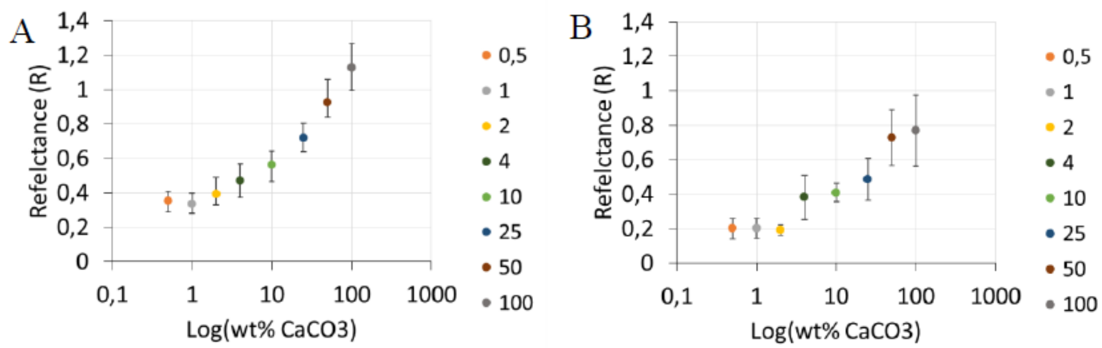


Figure 45. Laboratory results showing reflectance at 570 nm for dry sediments (A) and submerged sediments (B) with different calcium carbonate (CaCO3) content. Data points are average reflectance intensity from nine HI spectra, error bars show one standard deviation. (from Aarrestad, 2014)

Detection of carbonate content is one application where UHI data may be particularly interesting for MAREANO in the future, for mapping the distribution of bioclastic sediments such as the carbonate rich sediments originating from cold-water coral reefs (Bellec et al. 2014) and helping to verify to what extent acoustic data can indicate the presence of such carbonate rich sediments. Mapping of carbonate crust material linked to the escape of gas from the seabed is another related area of interest of relevance to MAREANO, where Aarrestad's lab results indicate promise, but remains to be tested with UHI in the field. Another area where UHI can potentially add valuable information for nature type mapping, or other applications is in the detection of organic content. The literature and laboratory results reported by Aarrestad (2014) indicate that this is another promising area for development, although it is noted that the absorption features from organic content and iron content can be difficult to distinguish in practice.

5.5 Evaluation of UHI data for biotope mapping

To produce full coverage maps of the distribution of biotopes, as required by management, predictive modelling techniques are used in MAREANO. These models use information on the characteristics and distribution of biological communities (based on visual documentation at MAREANO stations) and combine it with physical characteristics of the seabed identified by terrain analysis and geological interpretation. Since 2014, when oceanographic data first became available to MAREANO, these data have also been incorporated in biotope modelling.

The workflow for biotope modelling is summarized in Figure 46 (see also Buhl-Mortensen et al. 2009, Dolan et al. 2009, Elvenes et al 2014, Thorsnes et al. 2015)

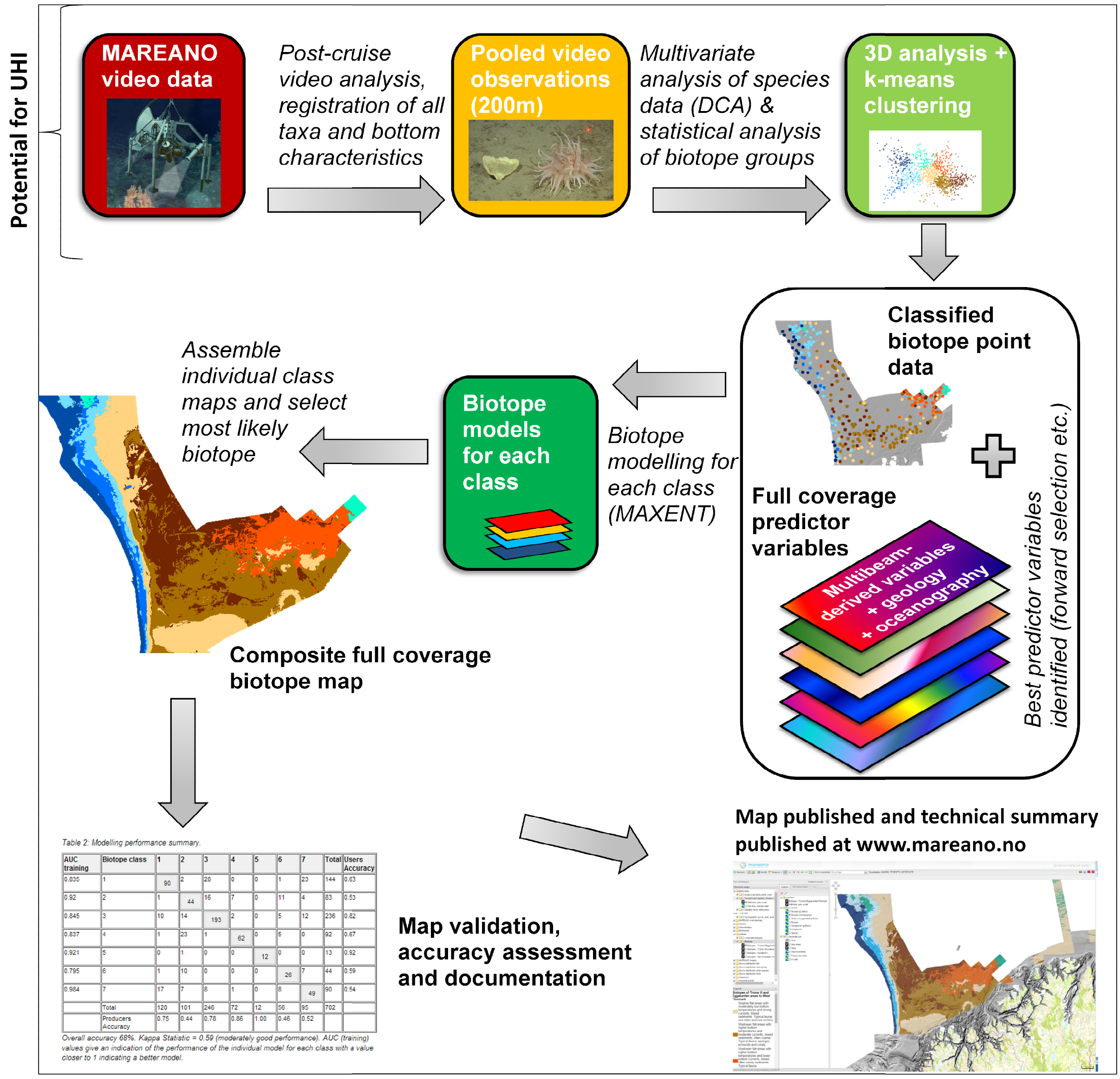


Figure 46. Summary of MAREANO biotope mapping workflow.

UHI data detects changes on the seabed at the metre scale and finer. We cannot expect UHI data to directly map biotopes over such scales but rather to serve as a supplement to traditional video data that provide the biological input to biotope models that use full coverage environmental predictor variables (bathymetry, sediment type, terrain attributes, oceanography etc) at resolutions of 50 m and coarser to predict the distribution of biotopes over a wider area (Figure 46). These maps largely capture broad-scale differences in biotopes between stations rather than finer scale variations within video stations.

The potential usefulness of UHI data for biotope identification or classification seems to hinge on whether these data can detect all benthic megafauna, or offer significant benefits over detection from video data alone. At present in MAREANO biotope mapping observations of benthic megafauna from video are subjected to multivariate analysis which leads to the delineation of biotope classes based on species composition. If, at some point in the future, characteristic fauna and/or bottom type(s) for each biotope class become firmly established then species data from standard lengths of video/UHI data could theoretically be used directly to determine biotope class. This, however, is not yet an approach that is ready to be implemented for offshore and deep-sea areas. Although becoming more well known through MAREANO the characteristic fauna and communities, and their associated environmental characteristics are not yet sufficiently documented.

MAREANO operates with a pragmatic definition of megafauna as those animals of a size detectable in video survey data when moving along a pre-determined line, not including animals detectable only during stationary video and with additional zooming. It is important to detect all taxa as the combined community over a certain distance is used to determine the biological communities and hence the biotopes used further in MAREANO modelling (Buhl-Mortensen et al., 2009). UHI detection of fauna relies on spectral libraries of known faunal signatures being available to aid detection. Until such time as comprehensive UHI spectral libraries are available it is difficult to see how UHI data can aid this part of the biotope mapping process. If at some point in time UHI becomes sufficiently developed for automatic identification of deep sea taxa that it can aid (e.g. by confirming visually ambiguous species) and/or replace standard video analysis (e.g. by automatic species recognition) then the data may become useful for biotope mapping.

It would be beneficial to the build up of a UHI library to develop an interactive interface for expert training of the UHI signature library. Since previously undocumented taxa are always expected to be found in new mapping areas there is always a need for manual annotation of videos. A software interface that enabled a trained video annotator to review suggested identifications based on machine-learning techniques, and make corrections/modifications could make video analyses less time consuming, more objective, and increase the confidence of the results. It would be equally beneficial to extend this expert training of UHI data analysis to sediment types and other objects of interest on the seabed. However, this would require both taxonomic experts and geologists to be far more hands on with the UHI data than has been possible as part of this study. As part of this evaluation MAREANO has only been provided examples of UHI filtered images, and selected spectral characteristics. Although Ecotone have offered access to the data via workshops this is not the same as the taxonomic, or sediment expert working actively with the data. We see clear benefits in such a partnership if a comprehensive library is to be built up.

In summary UHI data does not appear have to any proven advantages that can directly be used to aid biotope mapping at the present time although there is some potential for development. Since the identification of benthic organisms and bottom type are key prerequisites to the ability to classify biotopes and predict their distribution over a wider study area, and the need for development in both these application areas has already been identified in sections 5.2 and 5.3, it is difficult to comment on how UHI can contribute further to biotope mapping at the present time.

6. RECOMMENDATIONS FOR FUTURE DEVELOPMENT DIRECTIONS OF UHI TECHNOLOGY RELEVANT TO GEOLOGICAL AND BIOLOGICAL SEABED MAPPING.

6.1 Technical

Ecotone's hyperspectral imaging hardware is based on a patented hyperspectral camera and associated sensors and our focus in this report has been on evaluating this technology. We note, however that alternative methods for acquiring underwater hyperspectral image data are also in development elsewhere in the world. A recently published PhD thesis from the University of Sydney, Australia (Bongiorno, 2015) details the use of a spectrometer-based underwater hyperspectral imager. Although the study concludes that use of a hyperspectral camera is preferable to the spectrometer-based approach it also demonstrates the ability to acquire UHI data from an AUV and indicates promising results from the parallel (spectrometer-based) technology.

Ecotone's UHI data acquisition and data quality at the time of the pilot study was too reliant on the underwater platform employed. For example sudden movements of the ROV rapidly lead to poor UHI data quality e.g. Figure 36. Recent developments to address this issue are reported in section 6.5.1.

Preliminary experience from a test survey where MAREANO used AUV (Hugin) as a platform for acoustic and visual sensors (Thorsnes et al., *in prep*.) is that the visual sensor (a TFish colour image system) provides high quality imagery well suited for sediment classification. This is, in many cases, better than the imagery provided by the towed video platforms, because the problems with swell are eliminated. The suitability of AUV-acquired data for biological classification has not been assessed at the time of writing, but will be examined as part of the MAREANO assessment. The AUV was flown at an altitude of 5 - 7 m over the seabed, in order to assure no collision with protruding objects on the seabed. At present, this need for an altitude safety margin poses a challenge to using AUV as the platform for UHI because the distance between sensor and seabed becomes too large. Development of better anti-collision systems for the AUV, allowing operation with reduced distance to the seabed may overcome this problem. Another option is development of UHI systems capable of tackling a larger distance between sensor and seabed, but this would involve an additional challenge in terms of increased energy need for the lighting systems. Ecotone is currently adapting UHI for a range of marine applications and carriers (see section 6.5.1).

On a more general level, the results of the pilot survey indicated that the handling of UHI data volumes needs to improve such that round the clock operation of data acquisition, supported by rapid processing is standard. Particularly for offshore mapping 24/7 operation of survey vessels and data acquisition systems is common and this level of data handling would be essential if UHI technology is to be adopted on long, intensive cruises such as MAREANO's biological and geological sampling cruises which operate round the clock for several weeks at at a time. Ecotone have informed MAREANO that considerable development has been undertaken during 2016 to improve this issue (see section 6.5).

Based on the results of the pilot survey it was apparent that GIS integration of UHI data would benefit from improvement. The use of raster management tools (e.g. ArcGIS mosaic dataset) for RGB images and classified rasters is one potential avenue for improvement. This type of approach could make it easier for users to work with the data, providing faster display and one step colour management as well as providing an easy way to pool together images from each survey rather than working with individual image files which can soon become cumbersome. Classification of UHI data is currently done on a pixel-by-pixel basis but we note that methods based on object based image analysis (OBIA) for segmentation and classification of raster data may be beneficial as each pixel is 'aware' of the properties of neighbouring pixels (see review by Blaschke, 2010). This type of approach is already becoming relatively well established in both terrestrial (e.g. Duro et al., 2012) and marine applications (e.g. Lucieer and Lamarche, 2011, Diesing et al., 2014) for various data types and has also recently been applied to airborne hyperspectral data (e.g. Xiu and Bo, 2015). OBIA is currently being investigated by NGU for classification of acoustic data with promising initial results. We note that since the pilot study Ecotone are already working towards improved integration of UHI data in GIS with several developments reported in section 6.5.2.1.

In this study all processing, analysis and classification of the UHI data was done by Ecotone using in-house software, much of which is proprietary. Many end users working to map specific objects of interest may be satisfied with this workflow. However, we see clear advantages for taxonomic identification and sediment classification in providing scientific end users (e.g. HI biologists, NGU geologists) more hands on access to UHI data. This would allow scientists to query spectral signatures and annotate or classify data directly and contribute to the building of spectral libraries. A geospatial software interface (potentially a GIS Add-in) that allows such interaction with the UHI data could be a worthwhile avenue for development for Ecotone if scientific end users are a business priority. At present the processing and classification is too much of a 'black box' which is at odds with the need for scientific users to explore the data and document their workflow.

6.2 Biology

In order to advocate the usefulness of UHI for identification of benthic species we need to be sure that hyperspectral signatures provide additional information compared to ordinary spectral signatures (from photo/video). In other words, it needs to be demonstrated that where ordinary spectral signatures fail to demonstrate significant differences between species with apparently similar colours, hyperspectral images provide confirmation of such differences. If this can be statistically proven for all benthic organisms, or at least for important, visually ambiguous species or those very dependent on the very best video data quality (i.e. quality difficult to acquire in practice), this is a promising avenue for the application of UHI technology.

For UHI data to become more useful beyond exploratory, or targeted surveys, a comprehensive library of spectral signatures needs to be developed for seabed mapping of benthic fauna and flora in all water depths across a range of biogeographic regions (e.g. all Norwegian Sea areas).The pilot survey in Trondheimsfjorden did not provide an extensive selection of benthic species. Only about 35 taxa were observed and georeferenced during the cruise. This should, however, enable the first catalogue of signatures for these taxa to be developed, especially since several of them occurred quite regularly allowing for comparison of individual signatures and confirmation of typical results.

Statistical methods for comparing curves in a plot need to be investigated further as visual comparisons are insufficient for scientific validation. In addition, alternative indices for representing the signatures for individual species should be discussed and tested in consultation with taxonomic experts. The ultimate goal for using UHI data for species identification is the use of the spectral information in machine learning techniques that can be used to automate at least parts of the image analyse process that is needed for mapping of selected species and biotope characterization. A geospatial software environment where the taxonomic expert could interact directly with the UHI data and video data would be very useful in development of such a system (see sections 6.1., 6.3)

6.3 Geology

Ecotone have presented some promising results suggesting the potential capability of UHI to discriminate between sediment types. This was a first field result and has highlighted the fact that detection and classification of sediment properties using UHI is still in its infancy. Further research and development is required building both on these and further field results and the laboratory studies of Aarrestad (2014).

A library of sediment types needs to be developed before UHI data can be classified on anything other than an exploratory basis involving the examination of individual known sediment types and sample spectral characteristics. It will be useful to utilise such a spectral library for sediment types in conjunction with an equivalent library for benthic organisms such that OOIs of biological or geological origin do not become confused at the classification stage and instead are available to be analysed in parallel as required.

In addition, we see a need for sufficient data to be acquired for statistical verification of a link between sediment properties detectable with UHI and sediment properties from precisely georeferenced physical samples to be determined, across a range of bottom types. The influence of biofilm on the reflectance properties of sediments should also be investigated and the detection of organic content in the seabed sediments should be prioritised due to its relevance for benthic communities. In order for UHI data to have value in practice for mapping of larger areas, a link between the sediment properties identifiable by UHI over fine scales and those detected by acoustic (multibeam backscatter, HISAS 1030) or other mapping methods (e.g. LIDAR) over broader scales should also be investigated and verified. In addition, as for biological applications, the advantages of UHI over standard HD video need to be further proven. All these tasks would benefit from close collaboration between UHI hardware/ software developers and marine geologists, preferably with both being able to work in a common geospatial software environment to analyse data and build up spectral libraries (see also sections 6.1 and 6.2).

To our knowledge, no detailed research linking UHI spectral signatures with acoustic or physical properties of seabed sediments has yet taken place within the worldwide seabed mapping community, with few groups as yet researching and using UHI technology. Scientific proof of the potential benefits of UHI for geological mapping is required across a range of marine environments and this will require investment in fieldwork, data processing and analysis and consultation with marine geologists including geochemists and geotechnical experts.

6.4 Biotopes

Analyses of hyperspectral colour information and patterns is an emerging science that may offer great potential for mapping of sediment types and properties, but which requires further verification and technical fine-tuning across a range of marine settings. The use of automatic recognition of benthic taxa is also still very much in its infancy, both regarding the use of conventional colour spectra, patterns and multi/hyper-spectral imaging. There have been some interesting results representing a limited number of species (Clement et al 2005, Purser et al, 2009, 2013, York et al 2008), but application of a library suitable for detection of characteristic communities/biotopes does not yet exist to our knowledge.

If a spectral library can be developed for offshore areas that is sufficiently mature to be used for routine MAREANO–style surveys, and UHI sensors can be successfully mounted on MAREANO video platforms, then UHI could potentially contribute to improved methods for delineation of observed biotopes. This may be possible through the use of georeferenced RGB images/classifications rather than using video data alone, but at the present time is a long way off. Quantitative statistics extracted from UHI data on the organisms occurring and/or dominating may help to indicate the transition between different biotopes more completely than the current MAREANO method of distance-pooled video observations. Further, if machine learning methods can be developed to help taxonomic experts use UHI to speed up and provide more robust records of species occurrence then UHI data may have an even more important role in providing input data for biotope modelling. Again this is dependent on comprehensive spectral library being available and we recognise that this will take time and investment to build up.

We note also that using a predefined library without careful manual control would lead to the lack of records of “new” taxa, or mis-identifications of fauna or sediment type, so the ability to quality control and update both biological and geological libraries will be essential. Whilst current MAREANO biotope mapping requires all species in a survey area to be identified, UHI data may be better suited to mapping of nature types in accordance with Natur i Norge (NiN v.2.0) (Halvorsen et al. 2015). A summary of NiN and discussion of the potential future role of NiN in MAREANO is can be found in section 3.3.2 of Thorsnes et al. (2015) and will not be repeated here, though we note the need for further testing of NiN theory and guidelines for practical use in nature type mapping. Once NiN is fully developed for practical use, each NiN nature type will be characterised by typifying species occurring under specified environmental conditions, including sediment properties. If these characterising species (and/or sediment type) typical of each nature type can be recognised by UHI then these data may be able to be used directly as a basis for determining the nature type present. At the present time, a large volume of work on the analysis of generalised species lists is required to allow NiN to be fully developed and theory tested for offshore areas. The MAREANO biology dataset will be invaluable for this task. Once the theory has been tested, if hyperspectral signature libraries could be established for the sediment and characterising fauna of each nature type could be realised, then this is perhaps a more promising avenue for the application of UHI to nature type mapping than mapping of biotopes where all species have to be identified. With the requirement for all publicly funded nature type mapping to be conducted according to NiN after 2018 this is work that should be prioritised if UHI data is to have a chance of contributing from the outset, but which requires significant investment and close collaboration with NiN (led by Artsdatabanken), MAREANO and other related institutes and agencies.

6.5 Summary of development in progress at Ecotone

This section will respond to issues raised by MAREANO in section 5 - MAREANO evaluation of UHI data. A number of the items identified by MAREANO for further development are already under improvement at Ecotone, some directly as a result of this study. This section provides an overview of the main development initiatives Ecotone is currently working on and has planned in the near future. The majority of these will offer improvements that are potentially beneficial for MAREANO but these will require full testing and demonstration of readiness in due course.

6.5.1 Hardware development

The UHI has been further developed and improved since the MAREANO cruise in 2014. The following list summarizes the main developments on the hardware side, many of which will address platform compatibility issues and data handling.

- **Ethernet-connected camera:** The new camera uses Ethernet for control and transfer of data, which increases compatibility of the UHI with operating platforms.
- **Integrated computer:** A microcomputer has been built into the UHI for data processing and storage. This will facilitate autonomous operations.
- **Integrated Inertial Measurement Unit (IMU):** Internal attitude measurements for reduced dependency on platform sensors.
- **Reduced size and power consumption:** The new system is smaller and requires less power than the previous generation (max 35w).
- **Adjustable focus:** The focus setting of the UHI can be controlled via the microcomputer.

The new [2016] version of the UHI has been significantly upgraded since the MAREANO pilot cruise. Specific developments have aimed at making the UHI independent of the underwater platform, and maintaining highest quality data acquisition regardless of platform and conditions. The onboard control computer enables the UHI to operate autonomously when deployed on an AUV or towed platform. The computer handles storage of data, navigation logs from the platform and the UHI's own Integrated Inertial Measurement Unit (IMU). There is also an integrated video camera which provides the same field of view as the UHI. By using a standard 13-pin connector, it is faster and easier than ever to integrate the UHI on a new platform. It also enables the UHI to communicate over Ethernet instead of dedicated fibre optics.

Ecotone has also made improvements with light source utilization. Halogen lamps have been used since the conception of UHI, but LEDs are currently being tested. In addition to having lower power requirements and significantly higher light output, LED-lamps are also less susceptible to power surges (e.g. if an ROV struggles against the current). Ecotone has tested different LEDs for this purpose through participation on several surveys during 2015 and 2016. In general, using LEDs allows the platform to increase the altitude (and thus swath width) by several meters depending on the power of the lamp. On several occasions, UHI data have been acquired at 4-6 metres altitude and produced results comparable to those acquired with halogen lamps at 2 metres.

Ecotone is currently adapting UHI for a range of marine applications and carriers. During August 2016, the MarMine cruise to the Mid-Atlantic Ridge (Mohn's Ridge) was undertaken.

The cruise included several dives with AUV (and ROV), to depths of around 2500 – 2900 m, where UHI was successfully tested and demonstrated, proving UHI to be operational on an AUV. Ecotone are currently delivering UHI systems to a research project, for use on buoys in the Arctic Ocean (Arctic ABC project). Ecotone is also in the process of installing UHI in salmon farms for lice detection (Aas et al. 2016).

Based on feedback received by Ecotone from IMR's technicians, the UHI is, in principle, compatible with the Chimaera towed platform used on MAREANO surveys. The Chimaera has available fibres for additional sensors to use, but would require installation of an Ethernet adaptor to integrate the UHI. Ecotone have been informed that IMR already has plans to upgrade the Chimaera with Ethernet connectivity, and believe that this should facilitate full and straightforward integration of the latest [2016] UHI system. Ecotone considers that Chimaera would offer a good platform for the UHI due to its operational performance and stability. One issue of potential concern is the effect of variable height above seabed of the video platforms. Both Chimaera, and its predecessor Campod, are heavy towed platforms (c. 500 kg) responding directly to ship movement in the waves. This may lead to height above seabed varying between 1.5 - 2.5 m. Ecotone have indicated that this variation in height will not be problematic for the latest [2016] UHI system.

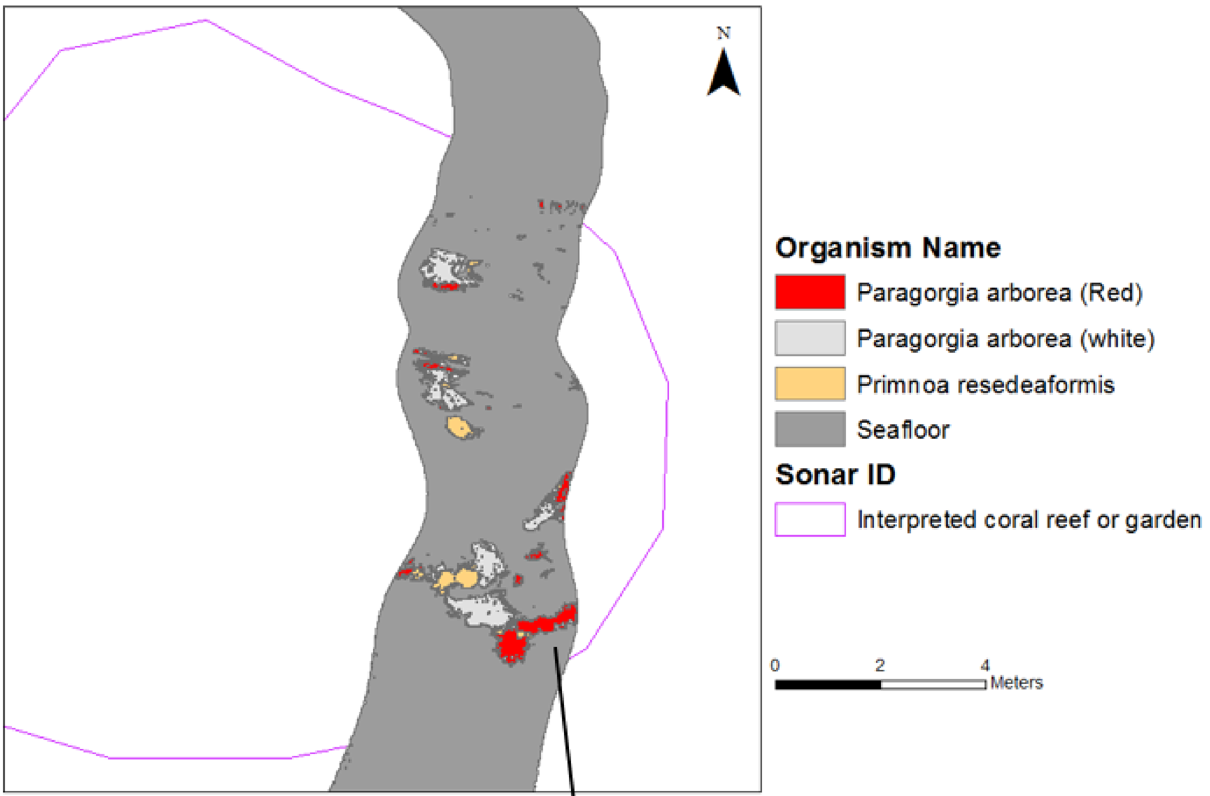
6.5.2 Method development

6.5.2.1 GIS and spatial integration

The UHI generated maps have received a significant overhaul since the conclusion of the data processing in this project. As emphasized in Section 5, MAREANO rightly points out that raster files usually are large in size and computer-intensive to display in context with other data. All classified UHI maps are now exported as shapefiles (.shp). A shape file contains a list of Feature Classes (a point, line, polygon or annotation) and associated metadata for each item in the list. Example of metadata can be *organism name, locality, area (m^2), coordinates* or *biological information (class, order)*. Since shapefiles are in vector format, both the draw time and file size are significantly reduced. The metadata are also used to generate dynamic legends in GIS. Multiple shapefiles can be combined into one large file containing all transects for a project, maintaining metadata for symbolisation and geographic properties. Thus, the issues raised in section 5.2 with NoData and symbolisation are now considered eliminated for classified data. Future maps from Ecotone will also follow the Seabed Survey Data Model standard (http://www.iogp.org) to facilitate easy integration and comparison with other data sets.

An example of a UHI classified vector file is provided in Figure 47. Ecotone participated in an environmental survey in the North Sea with a client, and prepared classification maps of coral reefs surrounding the area of interest. The legend in the figure is automatically generated from the metadata in the shapefiles, and overlays the client's interpretation of sonar data which indicates areas with a potential for coral reef growth. Three main classes of cold-water coral reefs were identified within this area, confirming the client's interpretation.

a) Vector map in ArcGIS



b) Metadata of *Paragorgia arborea*

Field	Value
FID	10056
Shape	Polygon
CLASS_NAME	Paragorgia arborea (Red)
AREA	0,5723
SURVEY_ID	10001
LOCALITY	
INSTRUMENT	UHI
Coral Order	Gorgonian

Figure 47. a) Vector map showing the outline of a sonar interpretation of a possible coral reef, overlaid with the actual UHI track and classification showing the appearance of three kinds of cold-water corals, b) metadata of the highlighted red coral Paragorgia arborea.

There is a mismatch between the scale of standard MAREANO data and UHI data. The high resolution of the UHI requires the user to zoom in close to display all the details, often beyond that of other data (i.e. bathymetry). There is also the absence of sensors with comparable resolutions where the closest is HUGINs HiSAS 1030 data at 4 – 33cm, currently not part of MAREANO standard data acquisition. This challenge has arisen for several of Ecotone's other clients as well, and Ecotone is considering several solutions to address this. One solution is to embed different displays at different map scales. GIS can change the visual representation of data as the user zooms in and out beyond predetermined map scales. For example, viewing a map in full extent could display UHI data as a simple polygon, line or point with annotations. Zooming in beyond a certain scale would reveal the high resolution UHI data. In both instances, the metadata are fully usable at all scales for spatial analysis.

The performance of the ROV affected the acquisition of UHI data. During this survey in December 2014, the ROV was at the maximum length of the tether (600m). The effects of currents on the tether and ROV, as well as drag from the boat, also influenced the manoeuvrability of the ROV. Acoustic positioning is limited to 1 Hz, and so when the ROV moves in anything but a straight line, the precision and accuracy of the positioning is affected. This requires significant post processing in order to fix, and relies on interpolation of data along the predicted path of the ROV based on the 1-per-second location input. This caused discrepancies between UHI data acquired at different times in the same area, and also with other map data.

A stable platform provides better conditions for acquisition of UHI data. This has become evident as Ecotone has participated on several surveys with working-class ROVs on depths from 300 to 1200m. All the ROVs had a Launch And Recovery System (LARS) or a cage. The stability of these ROVs have contributed to very smooth performance from the UHI on the recent surveys. Understandably, working class ROVs are not part of standard MAREANO surveys, but the experience of platform stability is transferrable to towed systems (such as IMR's own) and AUVs.

MAREANO emphasizes the need to have access to raw spectral information in the UHI data as part of its scientific endeavour. The spectral processing at Ecotone is performed in ENVI 5 as well as internally developed software before the vectorised files are generated for GIS. The spectral information is not exported in the shape files, but the geocorrected raster files that were initially produced can be exported with the full spectrum or three bands for simple visualization (RGB). To explore UHI data in a GIS-like setting with full spectral resolution, software like ENVI, or similar, is the current solution. Ecotone's current software development is focusing on the acquisition and pre-processing of UHI data. There are open source software like Opticks (https://opticks.org/) than can provide a free alternative to commercial packages for exploration of data. Ecotone is also developing a software suite that gradually will be opened up for scientific users who want to investigate the details of spectral signatures and explore new methods for classification of underwater objects and materials.

6.5.2.2 Species identification and classification

The basis for hyperspectral classification of organisms and objects in this project has been substantially supported by video and a list of observations made by Pål Buhl-Mortensen

(IMR). Ecotone is very well aware of the importance of validating spectral library input against knowledgeable sources and the current visual survey standard.

The key issues related to spectral classification of UHI data are related to the extraction of spectral signatures and their application across a survey line. The reflected spectral characteristics of biological organisms vary with how the object is imaged (shape, distance to sensor, lights). The pathway of the light through the water is also affected by the Inherent Optical Properties (IOP) of seawater, including effects of scattering and refraction by water molecules and dispersed organic matter in the water. By default, ENVI's spectral library function only records the average spectral signature for a class without accounting for variability within a class. Thus when the signature is used across a large transect, objects of that class get a better classification the closer they are to the average signature. So, objects of that class with a higher degree of variability in their spectral characteristics (due to position, size, distance to sensor) require more manual post-classification work to include it in the class. This is also where adjusting the spectral angle can overlap with other similar classes, and thus present a source of error. Class contamination is one of such errors, and results in spurious and isolated, wrongly classified pixels.

Post-classification methods have also improved the final classification result. Spurious pixels and class contamination, as described above, can be eliminated by applying cleaning techniques. Figure 48 shows one such example, where the sea cucumber is shown as it appears in the a) RGB image, b) the original classified version, and c) the new result following post-classification processing. In this particular example, ENVI performs a dilation and erosion operation of the two conflicting classes. This method uses the morphology of the object to determine if a pixel in question belongs to one class or the other. Dilation expands the class of the sea cucumber and "fills" the holes in the middle of the object, based on the class of the pixels surrounding the holes. Erosion removes the spurious pixels from the class 'rust', as they are isolated and erroneous occurrences.

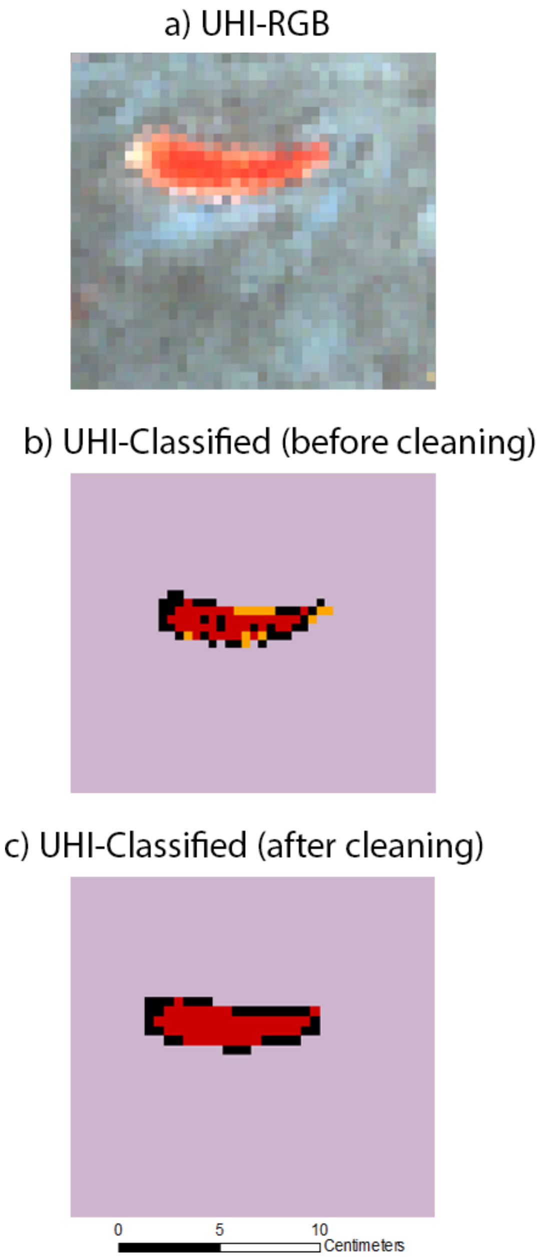


Figure 48. a) RGB-image of a sea cucumber, b) UHI classification image before any post-classification cleaning is applied, c) UHI classification image following post-classification cleaning; where the conflict between classes have been solved based on the morphology of the object.

A similar method to the one described above is to perform a majority/minority analysis. This method uses a user-defined kernel size (i.e. number of pixels surrounding the pixel of interest), and changes the centre pixel to that of the majority of the surrounding pixels. This has proven to be a useful tool in smoothing edges of classification polygons and also in dealing with areas with a large amount of spurious pixels. Figure 49 shows one such example, where cleaning of the classified image provides a more coherent image of the coral reef. Notice that the corals growing in between the larger specimens still remain classified.

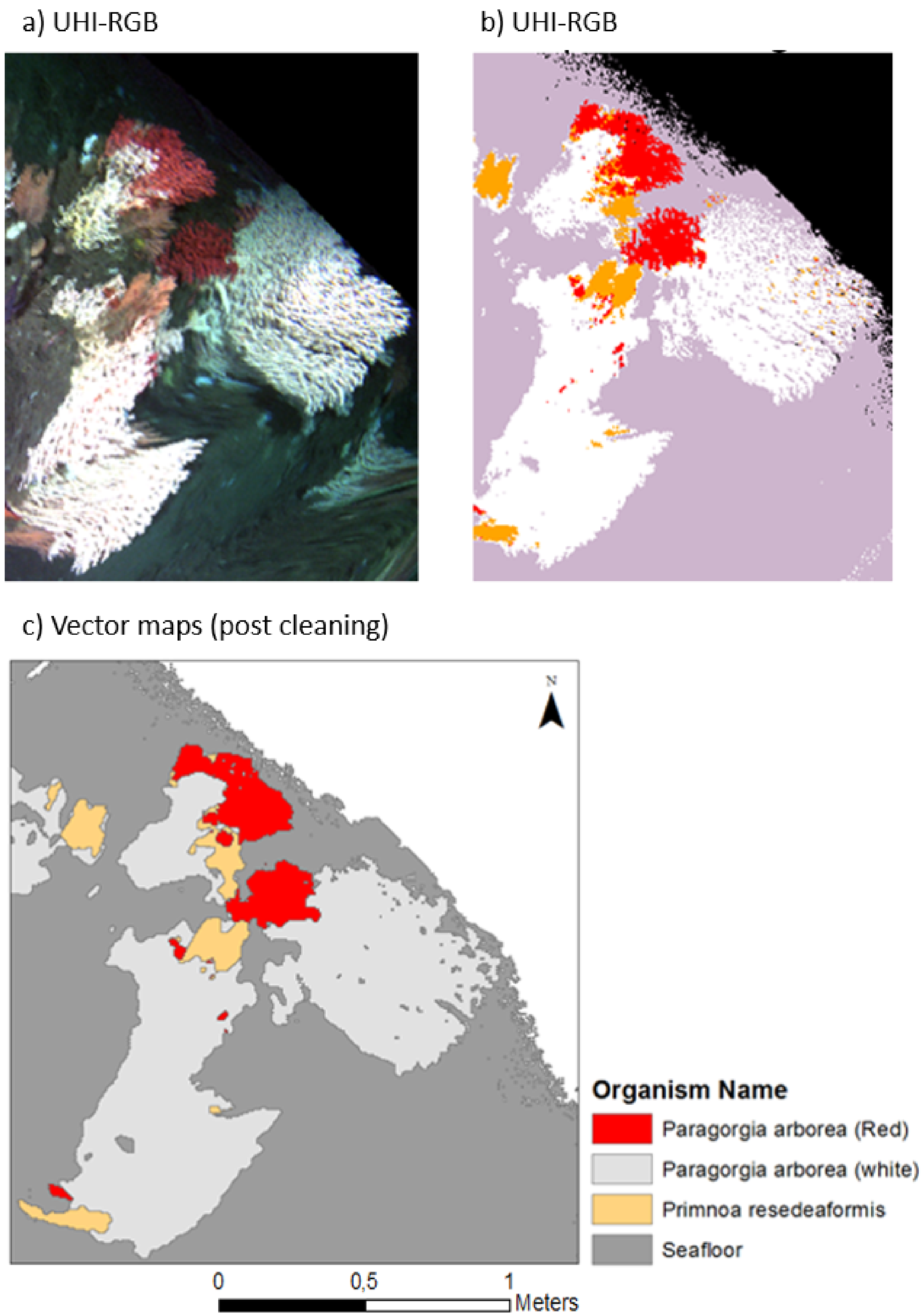


Figure 49. a) UHI-RGB image from a cold-water coral reef, b) UHI classification image before any post-classification cleaning is applied, c) vector image from ArcGIS after a majority analysis cleaning, smoothing the edges of polygons containing the separate classes.

Ecotone have taken several steps to address these issues and to improve classification. The internal software is able to export the average signature of a class (that can be made up by input from many OOI) and include the standard deviation of that class. The software can also compare the principal components of each class to determine their spectral similarity. Utilization of PCA (Principle Components Analysis) and PLS (Partial Least Squared) approaches have become a major part in the development of the classification tool. In transects where >95% may consist of seafloor without visible benthic fauna, reducing the number of components in the data is an efficient tool to identify unique spectral features. For example, if 95% of the data from the transect can be explained by the first or second principal component, the third and onwards can provide information on the remaining objects (Kobryn et al. 2013). This is a method that can provide an additional layer of information when distinguishing between spectrally similar species.

6.5.2.3 Biotope mapping

Ecotone foresees the possibility for the UHI to greatly contribute to biotope and habitat mapping. MAREANO correctly identifies the challenges related to such an endeavour, more specifically the scale that would be required and a spectral library. The latter is part of what Ecotone already intends to do and is working on. With regards to scale, for visual surveys a UHI generated habitat map could be used in tandem with other environmental data and maps to provide better characterization of a biotope. If we assume for a moment that a comprehensive spectral library has been used to generate a map of a large area (per MAREANO standard), the metadata from that map provides the means to group, categorize and select areas and organisms based on their characteristics. i.e. simple GIS-functions that let you select all species of *Parastichopus* within a certain range of other associated species. A clustering of species known to be associated with another in a habitat could be identified based on the numbers of those objects within a predefined geographical distance from another, for example types of sponges (*Geodia*, *Aplysilla*, *Hymedesmia*) or coral reefs (*Lophelia* occurring together with *Paragorgia*, and not just single appearances). Once rules for different habitat types are defined, it is a relatively straightforward task to implement this in a tool like ArcGIS to generate biotope maps based on UHI data.

6.5.2.4 Geology and sediment mapping

The use of UHI in sediment mapping and general geological application is in the early stages. The spectral signatures used in mapping of minerals in airborne application are found in the Short-Wave Infrared and beyond, outside the limits of the visible spectrum of the UHI. Thus, it is necessary to develop specific approaches to analyse UHI data with geological interests in mind. The philosophy behind the methods described in Ecotone’s report is based on a PCA of light reflected off the seafloor, and comparing the results across AOIs. This has provided preliminary results of interest, but will require further work.

The most interesting application of this method has been mapping the extent of sediment deposition following drilling operations. Drill cuttings and sediments smother the seabed close to the drill hole, and the degree and direction of deposition is influenced by the local currents. Ecotone analyses the spectral characteristics along a transect to detect a change in the sediment composition. An area smothered with sediment would have little or no benthic life and a homogeneous sediment composition, whereas an untouched area would be the opposite. A correlation coefficient for each area is calculated based on the similarity to a selected reference site, and is an indicator of the degree of change along the transects. Earlier in 2016, Ecotone acquired a complete data set of UHI transects before and after a drilling operation. The data processing and reporting is still ongoing, and will lead to a tool for comparison of fixed areas over time.

6.6 The way ahead for Ecotone

The potential application areas of UHI have expanded since 2014. The system has garnered significant interest from many parties, and Ecotone has several projects underway to explore new areas of application. Ecotone has performed pipeline mapping in the North Sea for a client, running 24-hour operations along 44 km of pipeline with speeds of up to 4 knots. The aquaculture industry sees the possibility to use the UHI to identify, classify and count salmon lice as an improved method for estimating the number of lice in a sea cage.

Ecotone is in the process of establishing underwater hyperspectral imaging as an approved methodology for environmental mapping with Statoil. Statoil uses a technology readiness ladder to assess the status and readiness of new technologies they are considering. UHI for environmental mapping is currently on a technology readiness level (TRL) 4 with a plan to reach TRL 7 by the end of 2016. TRL 7 is the final stage where the technology is approved for commercial use within all Statoil divisions.

Integration of the UHI on an AUV has been one of the founding ideas in the company. The advanced navigation system and sensor suite of modern AUVs improves on all aspects of an ROV-mounted UHI. This is especially true with regards to stability in the water column, Inertial Navigation System (ISN) for optimal navigation correction and connectionwith other sensors. Integration of the UHI on a Hugin class AUV has now been completed successfully by Ecotone, as reported in Section 6.5.1. Integration with other AUV classes will require implementation and testing, just as any sensor or camera system would do, however Ecotone do not foresee any major issues in doing that given the capabilities of the new [2016] system. The autonomous UHI implementation can communicate directly with the navigation system of the AUV, and the AUV can start and stop acquisition of UHI data based on its preloaded mission.

The new generation UHI [2016] has data acquisition and pre-processing software developed by Ecotone. With the inclusion of motion reference units (heave, pitch, roll) and other sensors in the UHI, the software will be able to log the required navigation data from internal sensors thus reducing the risk of time desynchronization when using external sensors. Position (at least on ROVs) is still provided externally.

The classification of objects based on spectral characteristics has improved and will continue to do so. Application of PCA and PLS explores UHI data more thoroughly and identify spectrally distinguishing features in objects, which Ecotone will use to improve the identification process. It has already been shown that small and almost invisible objects are detectable by UHI where video cannot always detect them, and the methods used to produce these results are continuously being improved. Special care is being applied to separate small and spectrally similar objects.

The new standard for classified UHI maps will be able to provide the user with more information than before. Ecotone will work to implement a comprehensive and robust system of metadata in the classification output, which will facilitate a highly detailed layer of information in a map data set. Classification of organisms can be tagged with information on their order or family, associated habitats and, for example, red-list status.

Ecotone appreciates the critical input from MAREANO (through NGU and IMR) during this project. Many improvements and developments have been the result of direct input from MAREANO during the last year and a half. MAREANO have highlighted areas where improvement is required in order for the UHI to be considered as a tool for the standard MAREANO survey, and Ecotone will follow this up closely. Ecotone will always remain open to future collaborations with MAREANO in order to improve the seabed mapping technology of the future, and the increased knowledge it can provide.

7. SUMMARY AND CONCLUSIONS

Ecotone AS, in collaboration with AUR-Lab, have successfully acquired UHI data and processed results that have given MAREANO sufficient opportunity to evaluate the current state of the technology for biological and geological mapping.

As a direct result of the UHI survey in Trondheimsfjorden Ecotone have:

- Demonstrated the technical robustness of the UHI as a part of the ROV sensor suite for the duration of the survey, with no UHI-related setbacks.
- Demonstrated the ability of the UHI to create GIS-compatible maps using UHI data with both RGB and classified images.
- Demonstrated the ability of the UHI to record data in parallel with a standard visual survey. This allowed subjective comparison of UHI and video data but results are not quantifiable due to differences in the camera angle and distance to object. An alternative setup may have allowed better video imagery data to be acquired.
- Demonstrated the ability of the UHI data through data analysis to reveal information from the seabed not visible in poor quality colour video. Many OOI require a trained eye to be detected on video, while the UHI has the ability to detect even the smallest and most obscure OOI within its field of view, after supervision from a trained eye or an established library of relevant characteristic spectra.
- Provided a glimpse of the potential of the UHI as a tool for the discrimination of sediment types. Further research and development are required.
- Mapped out the areas of improvement for the UHI system, with top priorities including integrated sensor logging and improvements of the spectral analysis workflow.

Ecotone and MAREANO have jointly presented results from this work at two international conferences. (a) Geological and Biological Habitat Mapping (GeoHab), Salvador, Brazil. 4-8 May, 2015, (b) Oceans MTS/IEEE Genova, Italy. 18-21 May 2015.

Throughout the course of this collaborative project a good working relationship has been established and maintained by all partners. This offers a solid foundation for any future MAREANO collaboration with Ecotone and AUR-Lab that may arise. MAREANO also acknowledges the substantial development of UHI hardware and software at Ecotone that has occurred since the MAREANO fieldwork in 2014 (see section 6.5).

Through fieldwork and subsequent evaluation of data from the 2014 Trondheimsfjorden pilot survey, MAREANO has reached the conclusions listed below. Where relevant development is already underway at Ecotone this is indicated. Note that further developments have not been tested or evaluated directly by MAREANO and are included for information only.

1. UHI is currently a supplement to, not a replacement for, standard visual surveys. UHI can provide supplementary information on biology and geology that may be useful to MAREANO in the long term as Ecotone's development of the technology continues.
2. UHI shows promise for several aspects of seabed mapping, particularly detection of biological objects of interest, however, based on the results of the pilot study the technology is not yet mature enough in terms of output products or data-capacity to be adopted by MAREANO at the present time. Some emerging UHI-related outputs (e.g. sediment classification) may be of future interest, but are not yet sufficiently developed nor scientifically proven (section 6.5).
3. The aspects of UHI technology with most proven results (e.g. rapid identification of selected target organisms) are not particularly well matched to the overall objectives and mapping scales of MAREANO (e.g. production of regional sediment and biotope maps at 1:100 000 scale and greater). Should MAREANO be required to undertake more detailed mapping, UHI technology may become a better fit, potentially in conjunction with AUV-based visual and acoustic surveys (see section 6.5 and Thorsnes et al., *in prep*).
4. The reliability and consistency of positioning of UHI data needs to be such that OOIs can be detected and classified based on data from adjacent lines, overlapping surveys. This issue was problematic in the pilot study but appears to be tied to platform stability and should be improved using working class ROVs, AUVs or towed platforms together with the latest [2016] UHI hardware and software as used in Ecotone's more recent fieldwork (section 6.5).
5. In order to be a cost effective supplement to standard visual surveys UHI must be deployable on MAREANO's main workhorse underwater platform. Modifications to IMR's Chimaera towed imaging platform are expected to make this possible (section 6.5).
6. UHI will be of more benefit to MAREANO once spectral libraries of species/sediment types are available for offshore areas. These libraries would be most rapidly developed by Ecotone in collaboration with MAREANO, potentially as a research initiative. This would be reliant on point 5, above where UHI is included as an extra sensor on the underwater platform. Acquisition of UHI data should be such that it does not impact standard MAREANO field-operations.
7. For the pilot study, data processing and classification was done by Ecotone and MAREANO assessment based on Ecotone-generated end products. Whilst this workflow was consistent with the project scope of work it was found to be restrictive in terms of scientific exploration of the UHI data. MAREANO have identified that UHI data should be provided in a more 'hands-on' format for scientific use, with access to spectral signature information directly in a geospatial software environment.
8. UHI data processing and classification times should be such that they are significantly less than manual analysis. Since the pilot survey Ecotone inform us that handling of transect and map data have been considerably optimized, with better processing of navigation data and automated ArcGIS workflows handling vector files, annotation and symbology of UHI data (Section 6.5.2.1). Relevant development for streamlining the processing is also underway in connection with the latest [2016] UHI (section 6.5)."

9. The potential benefits of implementing hyperspectral parameters in automated image analyses where other parameters (e.g. shape of objects and structure of patterns) are already used for automatic detection of selected species warrants further investigation.
10. As Ecotone continue their technological and product development ongoing input from MAREANO as a stakeholder would be mutually beneficial.

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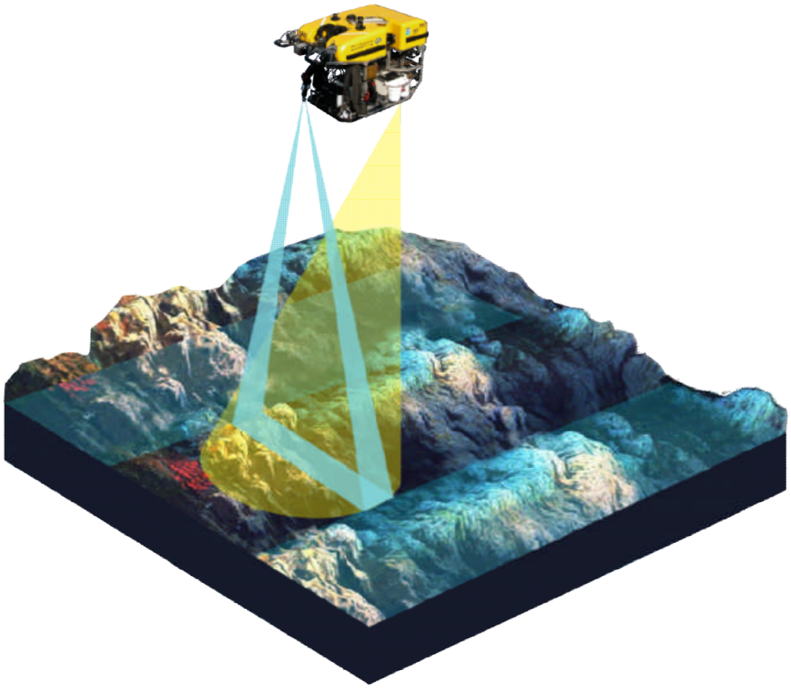
APPENDICES

Appendix 1: Ecotone AS report: Underwater Hyperspectral Imaging as a tool for marine environmental mapping

Appendix 2: Spectral characteristics and inter-species consistency

Underwater Hyperspectral Imaging as a tool for marine environmental mapping



Report #	1013/15
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Client	MAREANO represented by Norges geologiske undersøkelse (NGU) Havforskningsinstituttet (HI/IMR)
Date	18/06-2015
Authors	Stefan Ekehaug Lars Martin Sandvik Aas
Approved	Jørgen Tegdan

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Table of Contents

1. Introduction

The purpose of this report is to present the technology of Underwater Hyperspectral Imaging (UHI) in the context of marine habitat mapping in the MAREANO program. Data for the project was acquired during a survey in the Trondheimsfjord in December 2014 planned together with the Geological Survey of Norway (NGU) and the Institute of Marine Research (IMR). The area consist of soft-bottom habitats interspersed with ammunition and waste dumped at the end of World War 2. Three longer transects (500m) and a 20mx25m lawnmower transect were performed using Ecotone's UHI, mounted on an ROV deployed from R/V Gunnerus (ROV and ship owned and operated by NTNU). The data were processed according to Ecotone's standard methodology, but also includes examples of new developments where Ecotone's next generation software for underwater hyperspectral data were used.

2. Main Results

The field mission and the post processing of data were executed as planned. The results will be presented in detail in the following sections. The main findings and conclusions are:

1. The UHI performed as an integral part of the ROV sensor suite during the surveys, causing no operational issues. The UHI acquired data at the same time as the video survey. The survey speed and distance from the sea floor were determined by HD video requirements.
2. A number of benthic species were classified using UHI technology. The spectral signatures of the Objects of Interest (OOI) were recorded in field and used to build a spectral library. The library was used for automatic identification of living organisms and other objects on the sea floor. The potential of the UHI technology as a tool for more efficient marine mapping was demonstrated.
3. We were able to detect organisms with the UHI that were not visible on video. Features and objects can be enhanced by selective visualization using different combinations of wavebands. This is possible due to the high spectral resolution of the hyperspectral images.
4. As a part of the work on the report, UHI sediment classification were explored. The first results are promising. Principal Component Analysis (PCA) and statistical analysis successfully discriminated between sediment samples from four locations. At this point, the actual identification of the material still requires expert input and reference verification. This methodology is currently under development at Ecotone.

3. Background

3.1 Remote sensing in spatial mapping

Remote sensing is the science of observing and gathering information from afar. The modern usage refers to optical imagery acquired by aerial or satellite surveying, and is used in spatial mapping of both urban areas, the environment and the oceans (Kerr and Ostrovsky 2003; Berni *et al.* 2009). The remote optical sensors measures the incoming light reflected from a scene, where the information lays in light intensity and color distribution. The sensor may be monochrome, three-channel color, multispectral and hyperspectral. The difference between these are the amount of spectral (color) information. Increased spectral information can give higher confidence when discriminating between objects based on their color. Figure 1 illustrates the three classes of color vision. RGB, or three-color, imaging has three wavebands (same as the human eye), cameras comprising from three to typically 20 wavebands are classified as multispectral, whereas cameras with more wavebands are said to be hyperspectral. The color spectrum measured by a hyperspectral camera can in remote sensing application often practically be regarded as continuous. The high color resolution allows the camera to detect and discriminate between colors and objects not visible to a normal camera or human observer. Specific chemical signatures corresponding to internal electron transitions in materials can also be observed and classified as optical fingerprints.

The most widely used remote sensors are multispectral imagers, such as the ones used in the Landsat program and MODIS satellites (Kerr and Ostrovsky 2003). Multispectral sensors acquires information about the reflected light at specific wavebands (range of wavelengths). In the visible part of the spectrum, the wavelengths for red, green and blue (true-color) are used for earth imagery as well as certain features relating to the properties of each wavelength (Berni *et al*. 2009). An example of this is that blue light travels further in water and so is better suited for mapping deeper near-shore areas (Lee *et al*. 1999). Conversely, when mapping vegetation, the blue wavelength may be replaced with near-infrared given the high reflectance of vegetation in this part of the spectrum.

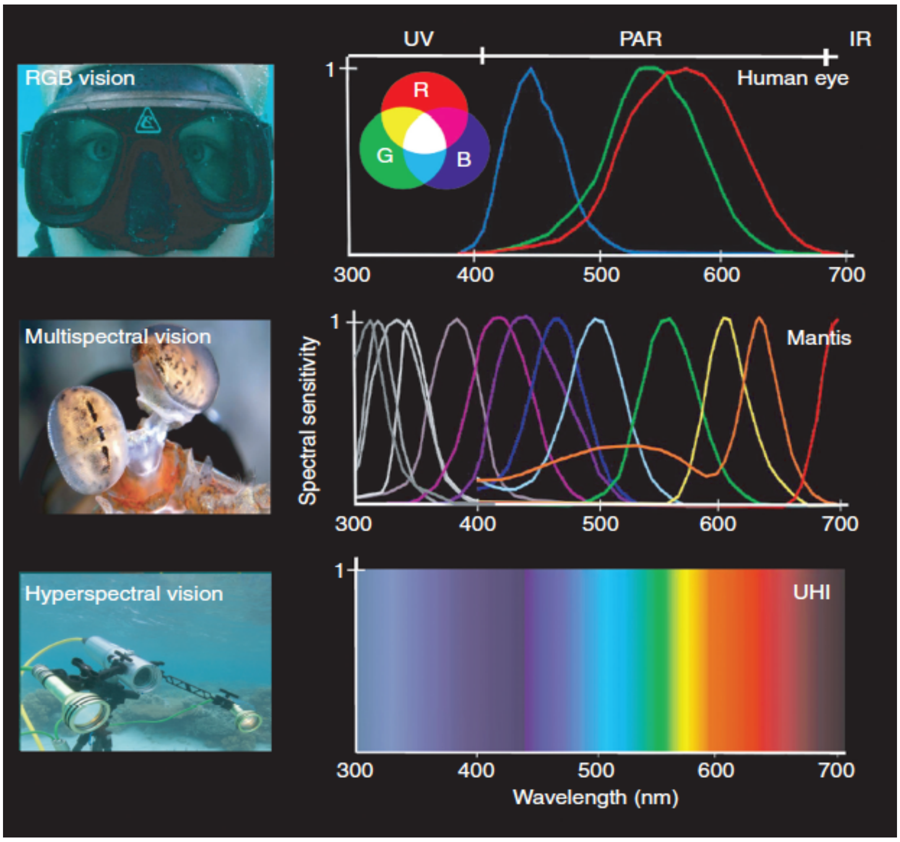

Figure 1. Comparison of human (RGB), multi- and hyperspectral vision.

3.2 Underwater Hyperspectral Imaging

With the UHI, the hyperspectral technology has been adapted from land- and airborne to underwater platforms (Johnsen *et al.* 2013). The challenges of underwater optics are mainly related to the natural optical properties of the water column. Water has a relatively narrow transparent spectral band that limits the use of UHI to the visible range. Even in the visible spectrum, water absorbs a large ratio of the light which limits the natural light available at larger depths (Brando and Dekker 2003). Consequently, the UHI platform must include external broadband light-sources where the cruising altitude is limited by the optical power of these sources and the variations in the water quality (Lee et al. 1999; Johnsen et al. 2013).
The UHI-system consists of the imager in an underwater housing and external illumination. As a push-broom line scanner, it faces the seafloor and records frames perpendicular to the direction of platform movement. Fiber-optics connect the UHI to a topside computer which stores all data and allows a live view and control of the UHI. The UHI have on several occasions proven to be able to record data in parallel with a visual survey.
To account for the variation in the optical properties in the water, Ecotone uses a 3D radiate transfer model to calculate the light scattering and absorption in the waters we operate. Work is ongoing at Ecotone to improve the algorithms used for classification to fully utilize the information in the visible light to perform classifications with minimal user input. This methodology will be improved upon using in-depth spectral and principal component analysis methods developed for this purpose and utilizing the underlying information in the spectral information more efficiently.

4. Methods

4.1 Location

Three longer transects (500m) and one lawnmower-pattern survey (20m x 25m) were performed at selected locations. The area chosen for the UHI-transects is located outside Agdenes, in the mouth of the Trondheims fjord (Figure 2). The site is notable for being a WW2 dumping ground for bombs, ammunition crates and associated artifacts, and these artificial objects have become part of the habitat for the local benthic organisms. Due to NGU's familiarity with the area through previous surveys with ROV and AUV and concern for the effect of the dumped material on the seafloor habitats, it was decided to perform the

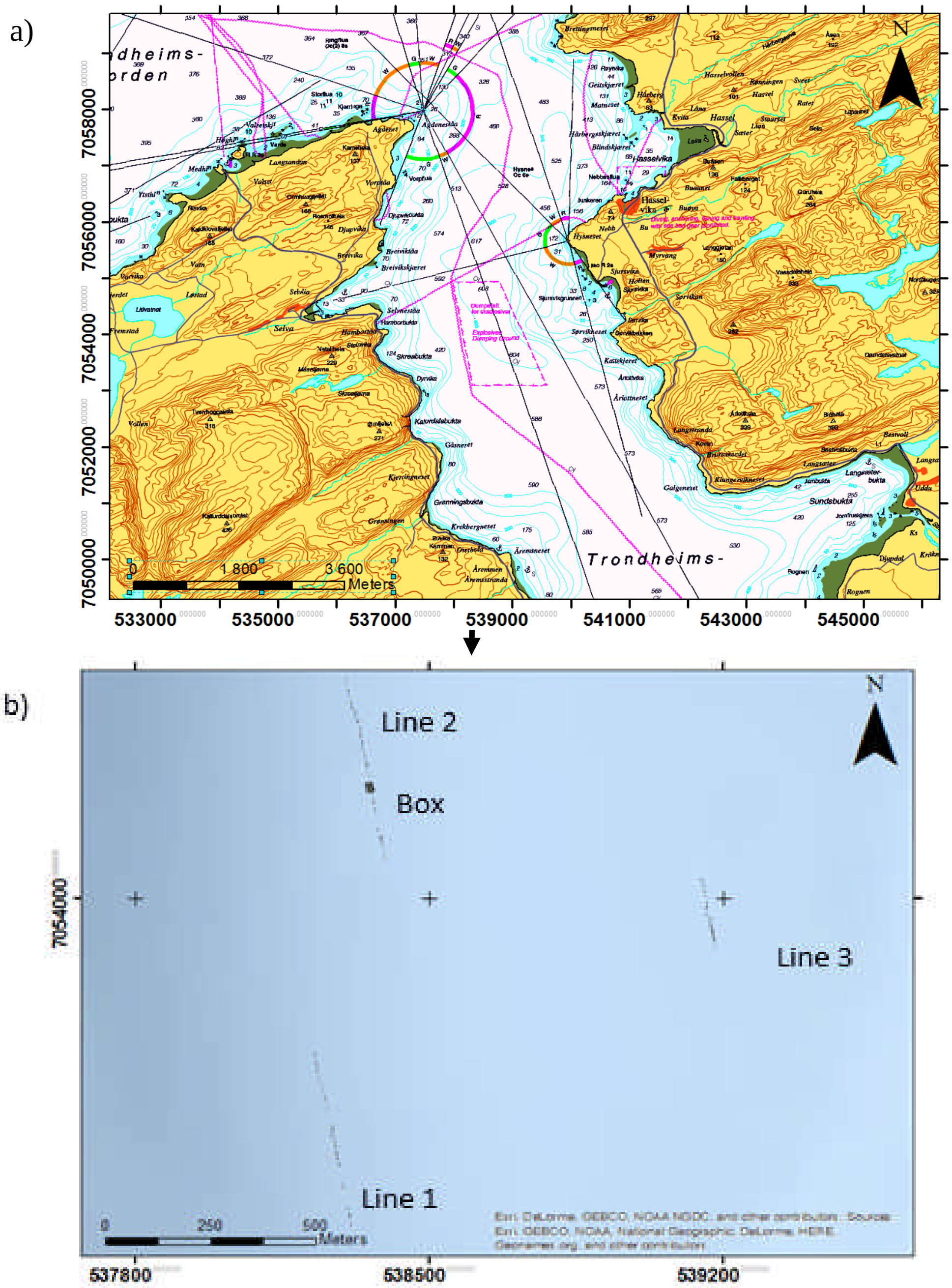

Figure 2. a) Map over the part of the Trondheim fjord where the transects were performed.

b) Zoom-image on the highlighted area showing the transects location relative to each other. UHI-recording at Line 3 was cut short due to the latter half of the transect going vertically up a coral wall.

survey here.

Table 1: Overview of the surveys performed during the survey.

Survey	Date and time	Start	Stop	Notes
Line 1 500m	Dec 10: 11:11-12:28	7053153.081, 538323.990	7053156.097, 538322.132	Restarted at 11:11 due to CTD recovery
Line 2 500m	Dec 10: 14:01-15:56	7054546.882, 538302.897	7054099.866, 538391.819	
Box 20x25m	Dec 10: 16:54-18:46	7054264.084, 538374.114	7054261.425, 538354.786	The ROV performed alternate transects backwards to counter the current
Line 3 500m	Dec 11: 09:49-10:53	7054048.242, 539150.382	7053838.559, 539191.392	UHI-recording difficult and cut short due to currents and umbilical problems. Standard classification not possible due to inaccurate logging in these conditions. Vertical mapping was not possible at this point.

4.2 Equipment

To accommodate the depths (600m) and physical environment of the designated location, the UHI was mounted on NTNU's ROV, a Sperre SUB-fighter 30K working class ROV (Figure 3). The ROV received a significant overhaul as preparation for the survey, and Ecotone was involved with the planning and finalization of the upgrades to ensure reliable UHI-communication and secure the imaging system along with light sources (2x 250w halogen lights from DeepSea Power&Light) in appropriate mounting brackets.

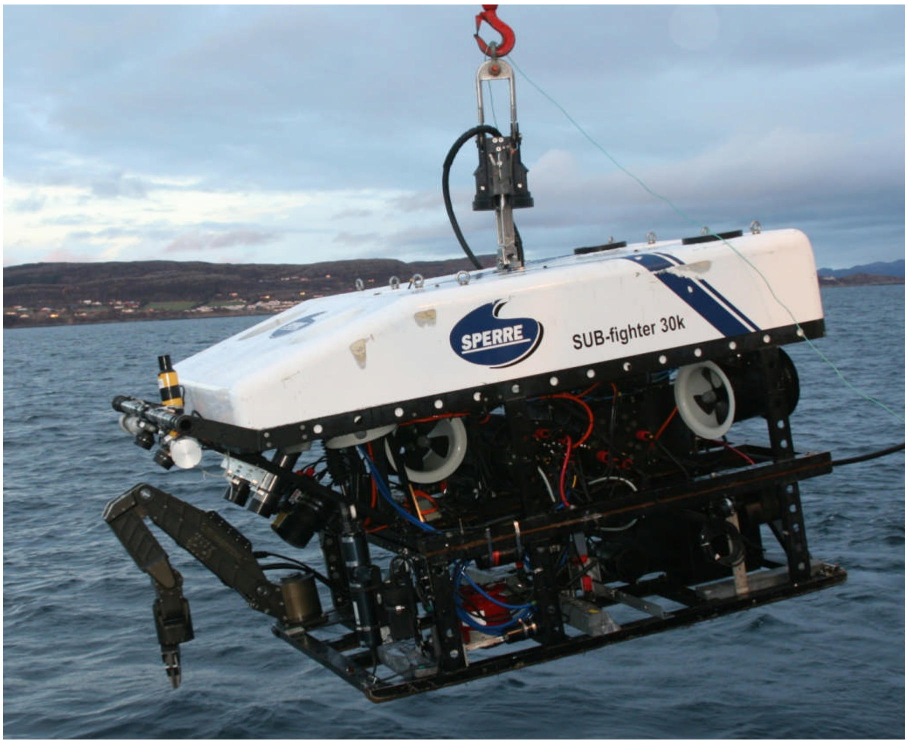

Figure 3. The working class ROV, owned and operated by NTNU, with the UHI mounted in the middle of the ROV frame.

4.2.1 UHI

The UHI was mounted in the center of the ROV, giving unobstructed field of view of the seafloor as well as protection. The light sources were fixed and flank the UHI at 35cm to each side. This provided even illumination of the field of view at the expected altitude for this survey. The UHI is connected to the ROV via a four-pin (two fiber optic, two power) hybrid cable, which provides both data connection and power. The UHI is controlled from the topside and the data is stored on the computer on board the ship.

A stable platform is essential in producing high quality UHI images. The line scanner acquires between 20 and 50 lines per second, and as such is very susceptible to movements. NTNU's ROV has the necessities to fulfill all the needs of the UHI, but the umbilical reached its maximum length at several instances. The drag on the umbilical through 600m of water were also an influence. This occasionally led to the ROV veering off course, especially when going too far from the ship or when the currents were strong. Consequently parts of the transects were dominated by stretch in the UHI spatial data.

Measurement of the UHI movement is obtained from the ROV's navigation sensors. The position, pitch, roll, heading, depth and altitude are recalculated to the UHI's position relative to the sensors. This information is later used in geocorrection when processing the UHI-images. The acoustic positioning system of the ROV and ship provides the position of the ROV (and UHI). The data is consolidated in navigation fileswith filtering applied to remove outliers if necessary. Unfortunately, there was only manual time synchronization between the UHI and the ROV computer, which introduced shifts in the logging, especially with sudden and fast ROV movements.

4.3 Data processing and analysis

4.3.1 Processing

The data was processed using Ecotone's software for radiometric calibration and apparent reflectance measurements. This process corrects for internal (sensor) and external (water column) influences on the image, and aims to present the apparent reflectance values of the objects in the image. Ecotone uses a 3D radiative transfer theory model to calculate light scattering and absorption. The position of the lamps during the survey are entered into the model and subsequently used in the reflectance processing. Accurate altitude and pitch/roll measurements are important in this process, to ensure quantifiable data across the different data files and transects. This process has proved to work well with the current light models. The radiometric and reflectance processing required approximately four hours per transect when run on a standard i7-laptop.

The UHI-images were geocorrected using the navigation logs. This process involves assembling the lines in the order and positon they were acquired, and adjusting for ROV-movement to ensure accurate coordinates for each pixel, and thus, objects. The ground cover for a pixel after geocorrection varies with altitude. An example of a log file is shown in Figure 4. Filtering has been applied to the positioning data to remove outliers or false data points (i.e. the ROV jumps 5 meters in one second). Additional improvements were developed and applied to fix image artifacts (Figure 5).

```
;UHI Navigation File
;UTM Zone 32 N
 10-12-2014  10:42:00.0009  7053103.926 538326.9087 1.163104    4.194051    -48.959244  584.32685   1.1596
 10-12-2014  10:42:00.1419  7053103.939 538326.8692 1.254778    4.314372    -50.053593  584.309245  1.1602
 10-12-2014  10:42:00.2599  7053103.952 538326.8305 1.266237    4.4748      -51.291182  584.288181  1.1643
 10-12-2014  10:42:00.4239  7053103.966 538326.7928 1.294885    4.543555    -52.471475  584.2664    1.1715
 10-12-2014  10:42:00.5679  7053103.981 538326.756  1.174563    4.967544    -53.583013  584.238568  1.1816
 10-12-2014  10:42:00.7359  7053103.986 538326.7307 0.790682    4.560744    -55.490962  584.219637  1.2001
```

Figure 4. Example log file for use with geocorrection, in this case from Line 1. In the columns from left to right: Date, Time, Position (N, E), Pitch, Roll, Heading, Depth and Altitude. The values have been resampled to 7 Hz by NTNU.

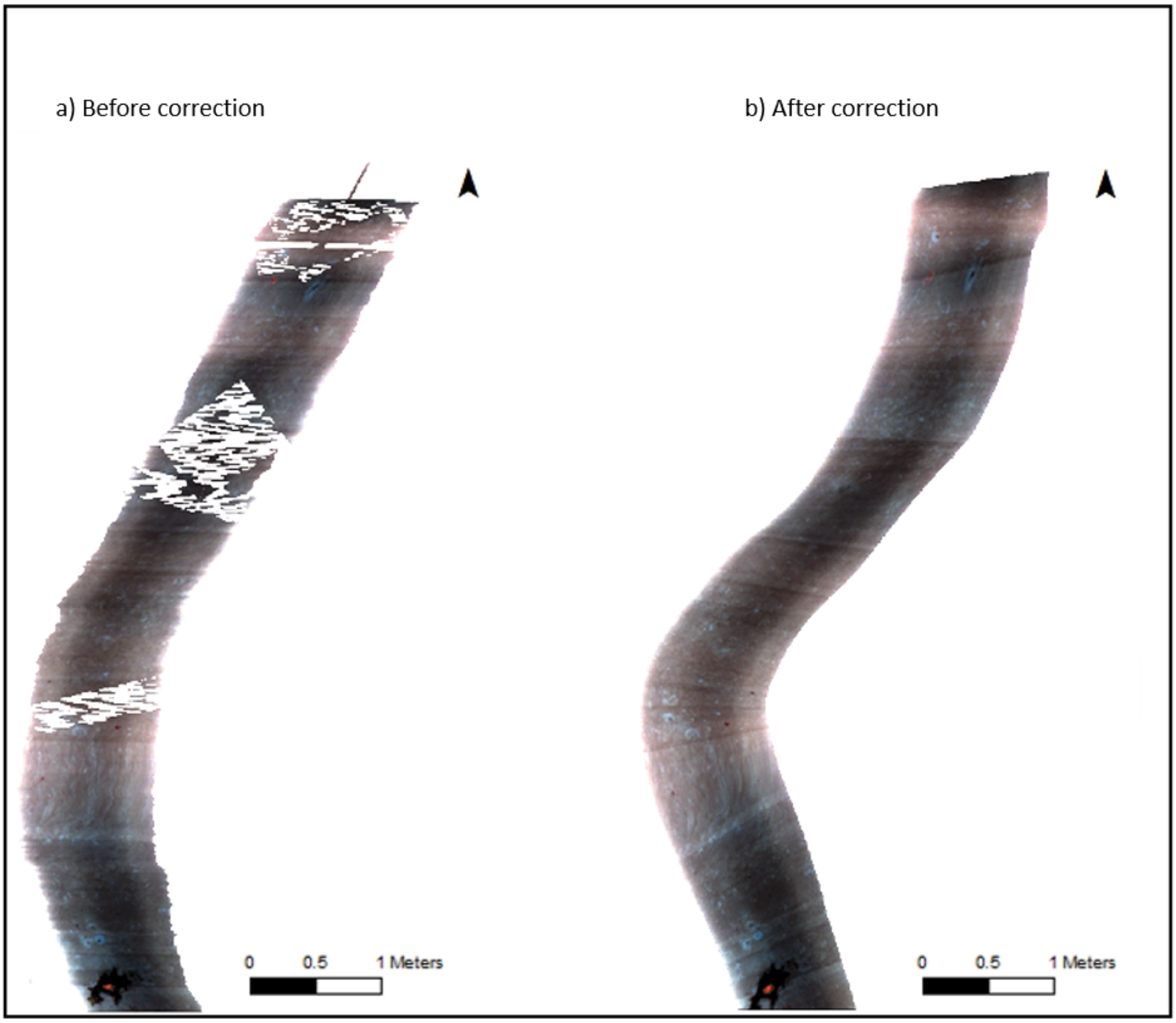

Figure 5. Excerpt from Line 1, showing the UHI-file before (a) and after (b) smoothing of the navigation data used for geocorrection. The artifacts in A have been eliminated.

4.3.2 Classification

Classification was performed using spectral processing software, both commercially available and in-house developed software. At the point of the survey and the subsequent post-processing, the main software was ENVI 5.2. ENVI has been used for the biology classification and production of UHI-maps, with both Ecotone's own developed extensions and built-in tools. In addition, several iterations of the internal software development at Ecotone have been applied.

Classification in ENVI was performed using the results from Spectral Angle Mapper (SAM). This algorithm determines spectral similarity by calculating the spectral angle between the spectra of interest and the reference spectra, by projecting them as vectors in a space with dimensions corresponding to the number of bands (Figure 6) ((Sohn and Rebello 2002; Kruse *et al.* 2003). An advantage of SAM is that it is insensitive to changes in illumination between the compared pixels. Darker pixels will fall closer to the origin point than illuminated pixels, but the angle between the vectors is still the same. It should be noted that the default SAM in ENVI does not include spectral variability within the classes, instead using one reference spectra for each class (Kruse *et al.* 2003). Classification using SAM in ENVI on a standard i7-laptop required approximately 12 hours per transect.

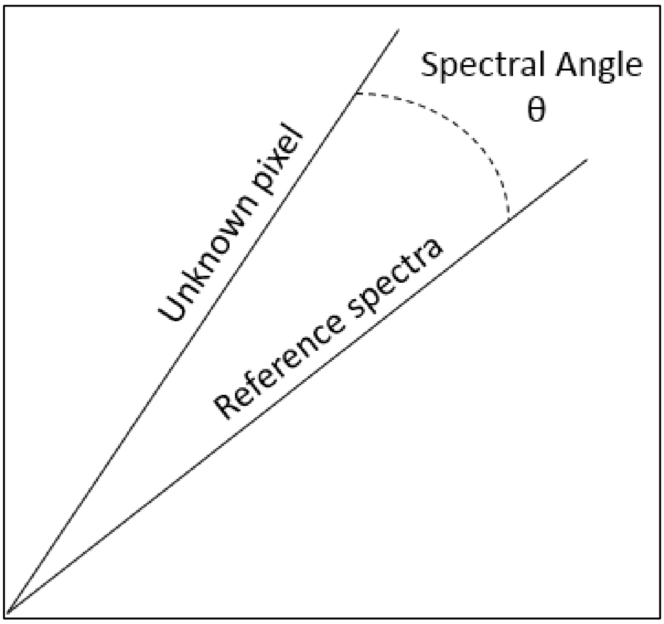

Figure 6. Spectral Angle Mapper uses the spectral angle between two projected vectors in n-D space to calculate the similarity between a reference spectra and an unknown class (Sohn and Rebello 2002).

The reference spectra were created by selecting a group of pixels covering the OOI. At this stage, it is done manually in ENVI. An average of all the pixels for one class was stored as a spectral signature in a spectral library file. This file was then used as a reference when SAM is performing the classification. If the projection of an unknown pixel is within the spectral angle of a reference spectra, it will be assigned to that class.

The spectral angle can be adjusted to match the data distribution. A default value is applied to all classes, but each class can be manually adjusted. This is necessary to minimize class contamination, especially when working with rare classes where an increased angle can quickly include pixels from other similar objects (false positive). This is performed manually at this stage, and the user adjusts the angle for each class after evaluating the results.

In addition to using de facto standard software tools for conventional remote sensing, Ecotone is developing a specialized software for underwater hyperspectral imaging analysis. The software suite is currently on an experimental level, but to demonstrate some of the future possibilities it was decided to also use some of these functionalities on some of the data in the current project.

One method used is based on Principal Component Analysis (PCA) (Pearson, 1901). The spectral components are decomposed into eigenvalues and eigenvectors. One can then disregard spectral components that are not important (associated with e.g. high frequency white noise). We show in this report that the method can be used to focus the analysis on spectral components relevant for sediments, or biological organisms with useful information.

5. Results

5.1 Visual Survey

5.1.1 Box transect

The results initially show that detection and classification is successful on larger and more abundant objects and organisms in ENVI. Some of these results are highlighted in this section, and the position of the examples used are marked in Figure 7. Some organisms showed accurate classification on the main part of the body, but around the edges there were some instances of class contamination. Conversely, smaller and rarer objects suffered from misclassification without appropriate threshold adjustment in the classification process.

a)

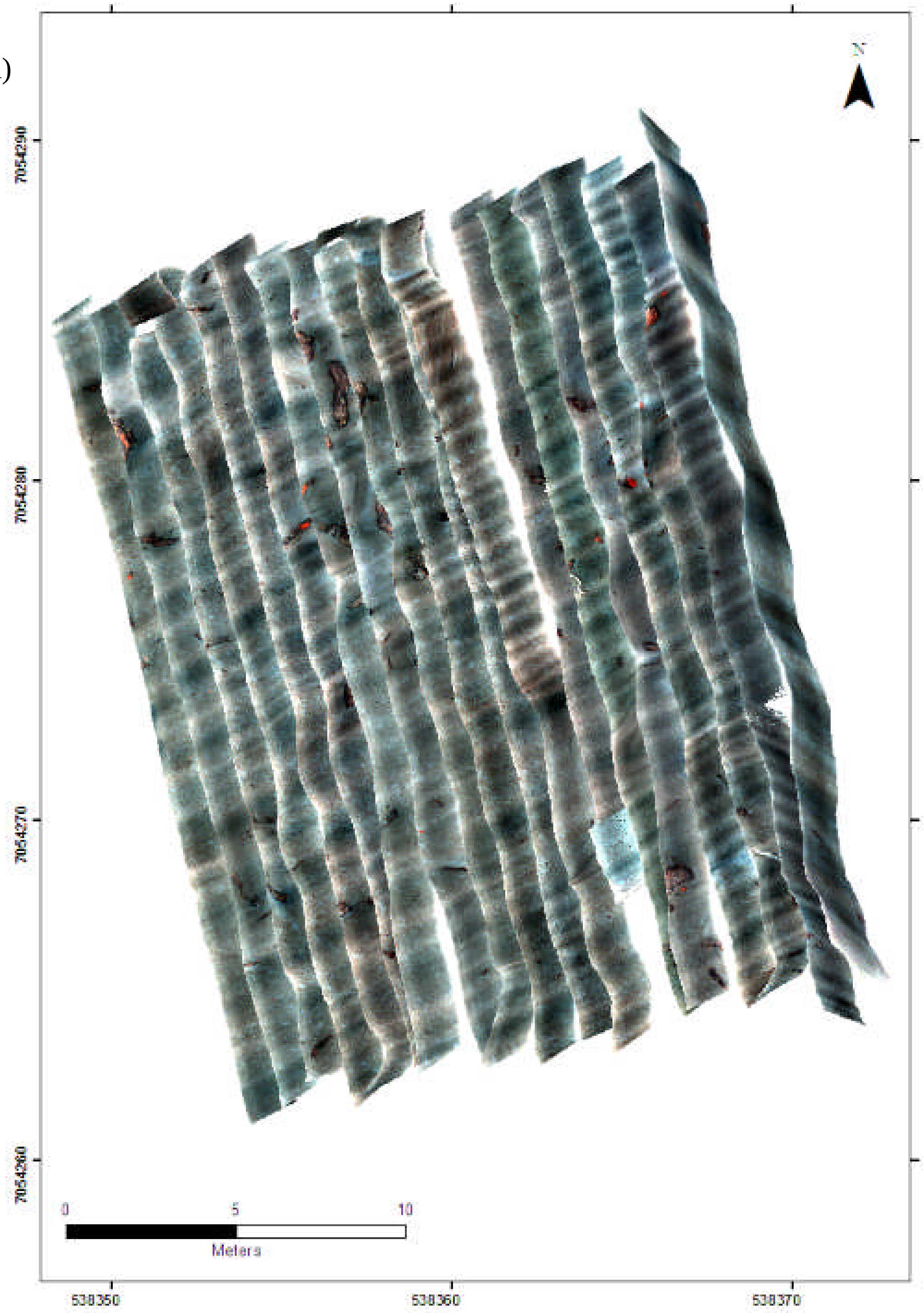

Figure 7. a) UHI-RGB image of the box transect. b) Spectral Angle Mapper-classified mosaic with the upcoming figures marked on the map. The white areas in the maps are where the transects did not successfully overlap due to ROV-movements

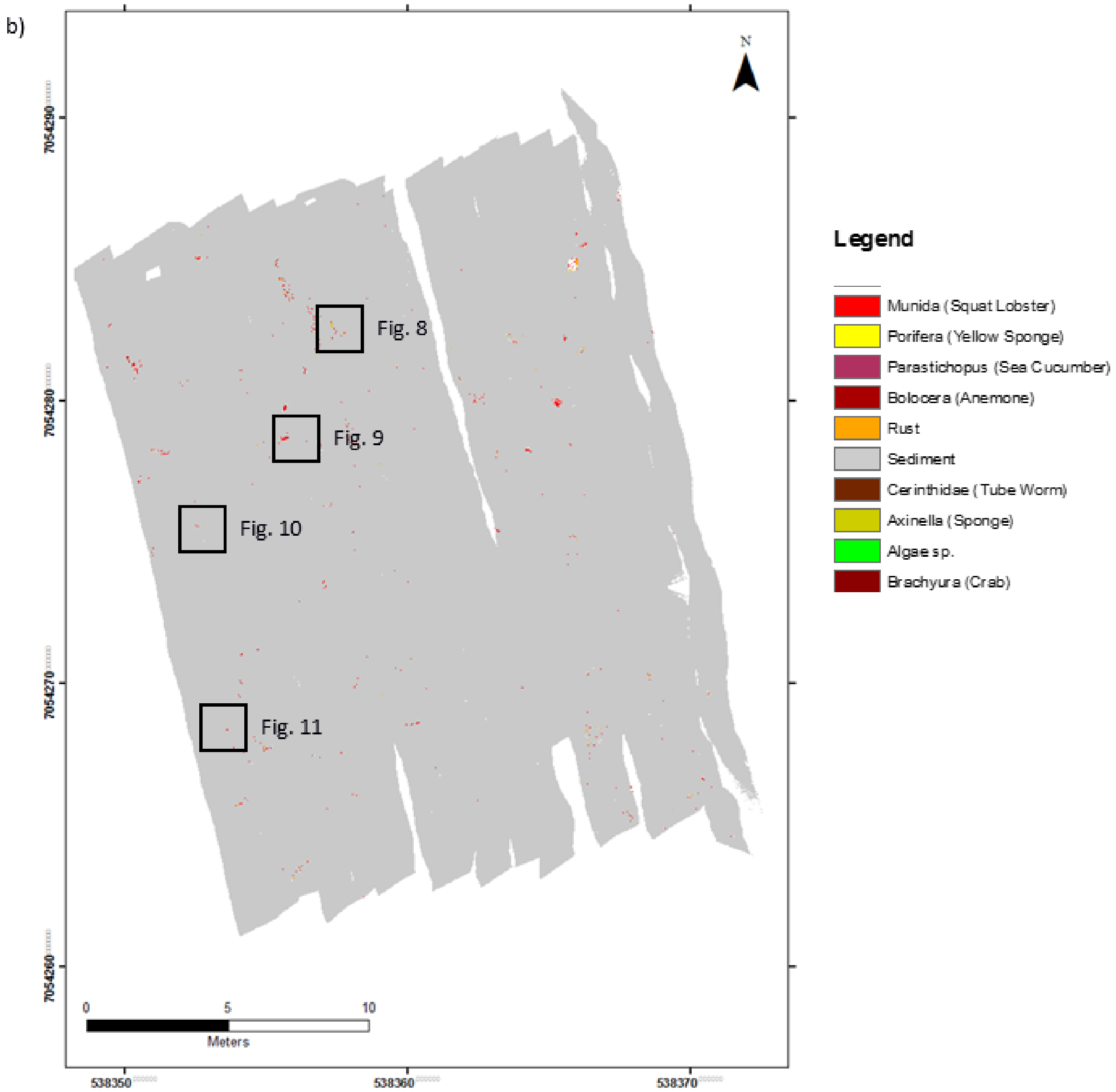

Figure 8. a) UHI-RGB image of the box transect. b) Spectral Angle Mapper-classified mosaic with the upcoming figures marked on the map. The white areas in the maps are where the transects did not successfully overlap due to ROV-movements.

Figure 8 shows the sponge *Axinella* growing on a manmade object. The classification appears to be very accurate, attaining the shape and form of the organism as visualized in the RGB image. Some contamination can be seen on the long pole-like object. The rust surrounding the sponges are also well matched, though somewhat conservatively. The bottom image in the figure shows the same scene, through Ecotone's internal software. The scene has had the first three eigenvalues removed, reducing the spectral data mostly made up of background sediment. The result highlights the spectral appearance of the sponges and the surrounding rust.

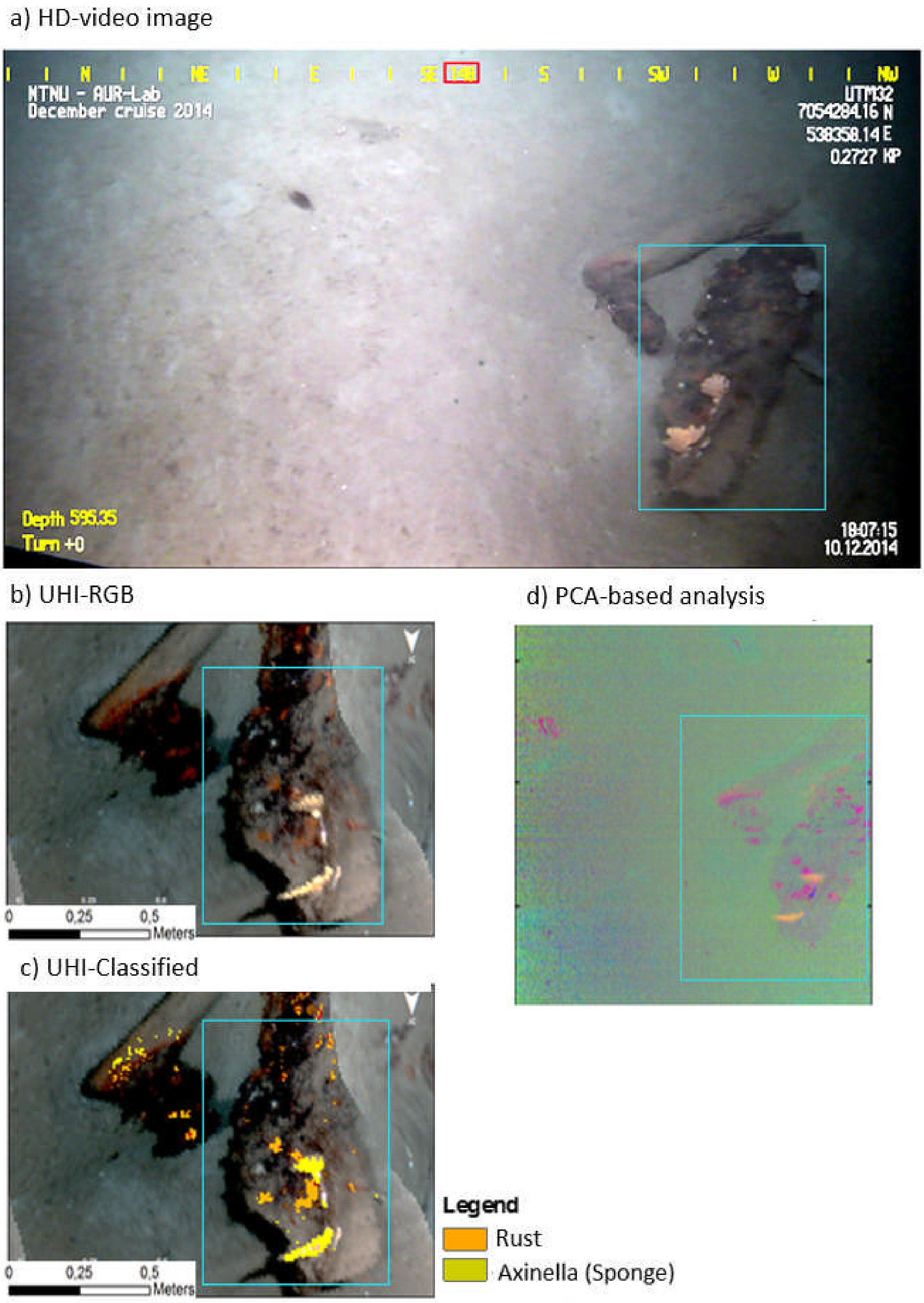

Figure 9. a) Video still showing the sponge Axinella growing on a manmade object, b) UHI-RGB image of the same sponge and the surrounding rust patches, c) UHI-RGB image with classification overlay, d) image from Ecotone's software with three eigenvalues removed.

The sea anemones returned some of the best classifications. The size of the main body is accurately classified across the transects. However, the tentacles of anemones are classified as separate OOIs. Figure 9 shows that the main body is correctly classified, whereas the tentacles have a tendency to not fall into the anemone class. Depending on the spectral angle threshold, it may fall into another similar class. This can be expected of the anemone, as the tentacles are freely moving and of a different color than the main body. The former is most likely the reason that classification of the tentacles remains challenging.

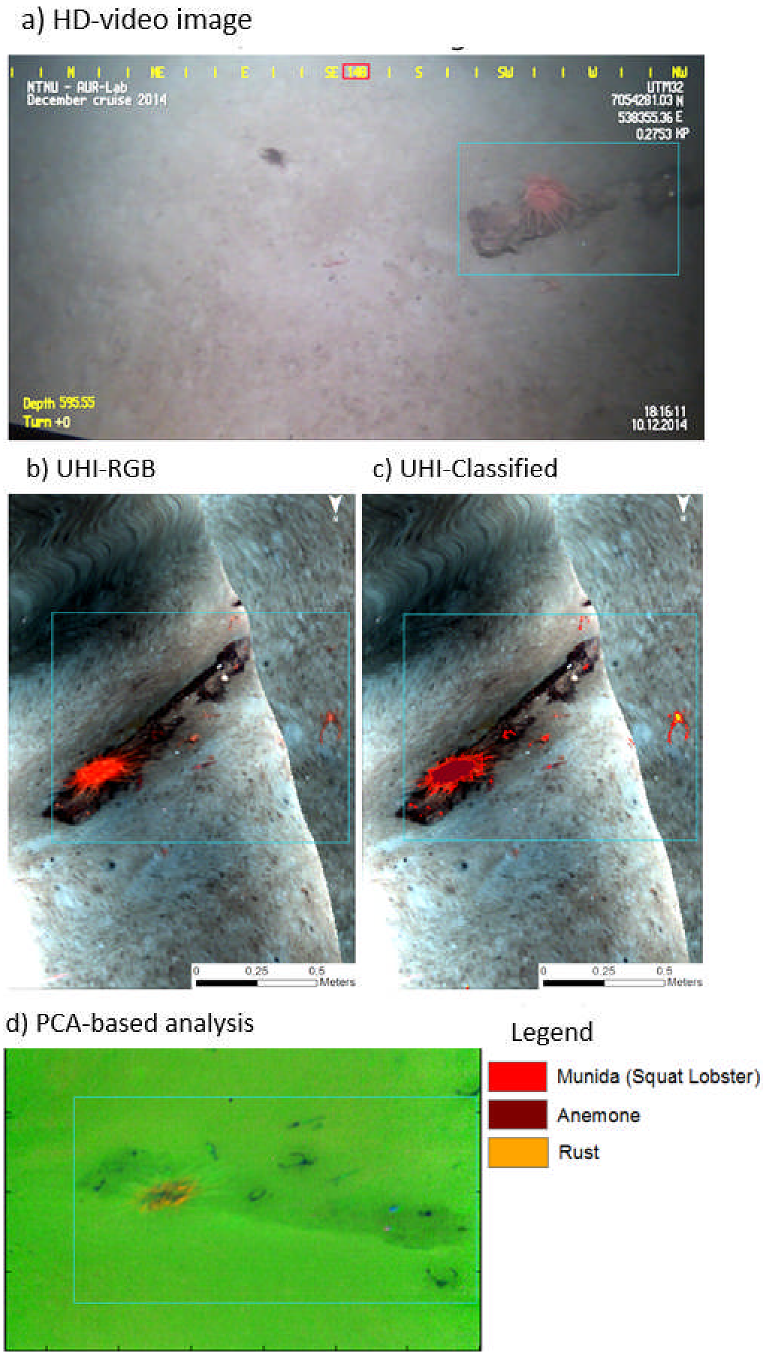

Figure 10. a) Video still showing an anemone (Bolocera sp.) sitting atop a manmade object, b) UHI-RGB image of the same anemone and surrounding squat lobsters, c) UHI-RGB image with classification overlay sowing identification of sea anemone and squat lobster, with some class contamination on the Squat lobster (from class Rust) and on the tentacles of the anemone, d) image from Ecotone's software with two eigenvalues removed highlighting a number of lobsters not visible on video or UHI-RGB.

The common sea cucumber (*Parastichopus*) is easily visible on both video and UHI. The classification success is largely based on this significant deep red color. As can be seen in Figure 10, the top part of the animal showcases strong adherence to the correct class. There is some class contamination around the edges of the body, from the classes rust and squat lobster. During the ENVI-analysis of n this particular image, we noticed three pixels classified as squat lobster next to the sea cucumber, though initially was not discovered neither on UHI-RGB or video. Eight eigenvalues were removed to reveal a very small squat lobster, around 1cm in size.

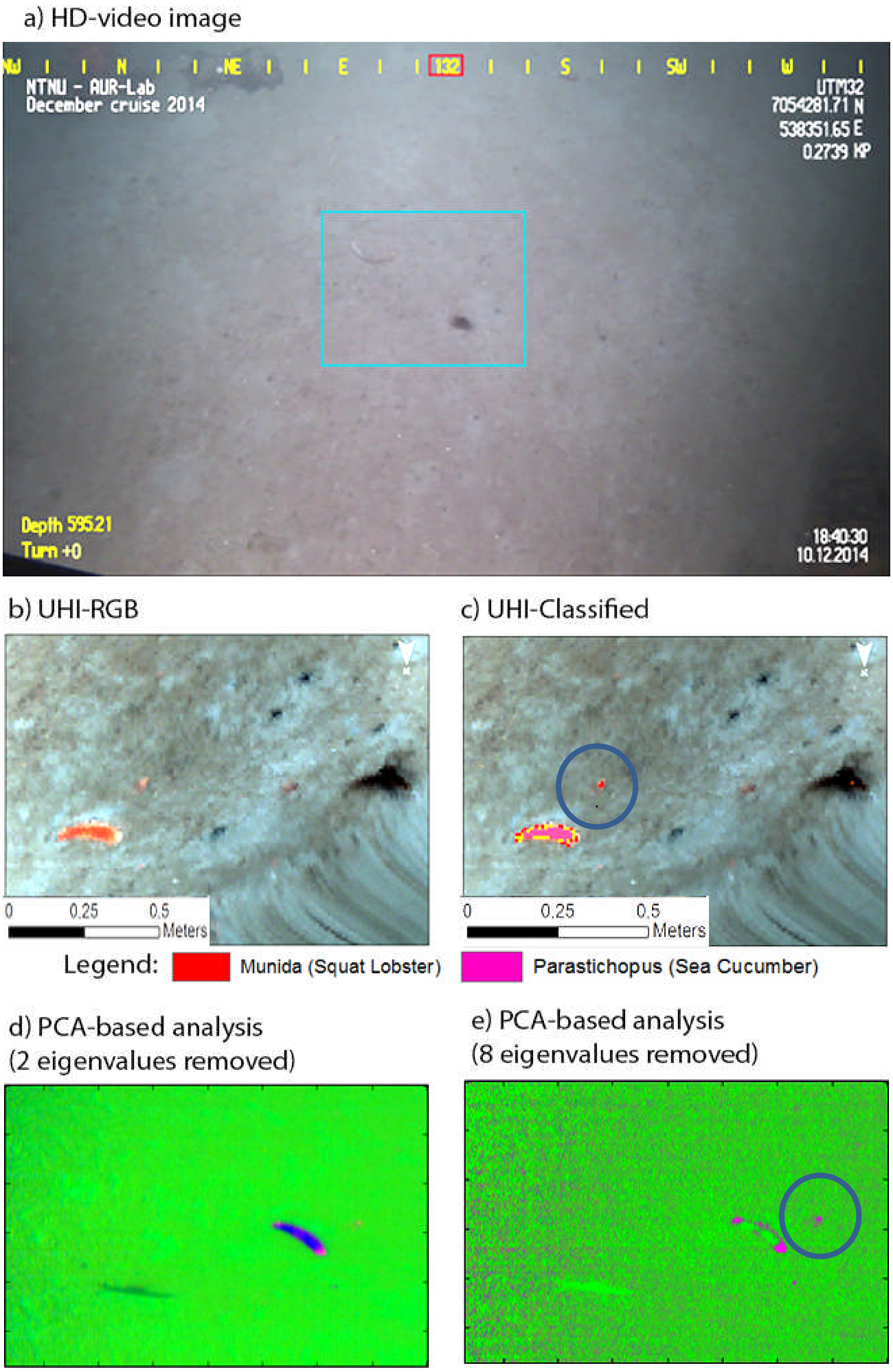

Figure 11. a) Video still of a sea cucumber, b) UHI-RGB of the same sea cucumber, c) UHI-RGB of the same sea cucumber with classification overlay. Notice the three pixels just above the sea cucumber representing the squat lobster class (circled), d) UHI-image with two eigenvalues removed highlighting the sea cucumber, e) UHI-image with eight eigenvalues removed revealing the tiny squat lobster next to the sea cucumber (circled)

There were instances where the UHI detected severa l OOI not recorded in the video log. Figure 11 shows a manmade object that appears to be deserted in the video still image, but both the UHI-RGB and the image processed with Ecotone's internal software shows at least nine squat lobsters on or around the object. None of these were visible in the video without pausing and zooming, and so did not appear in the log.

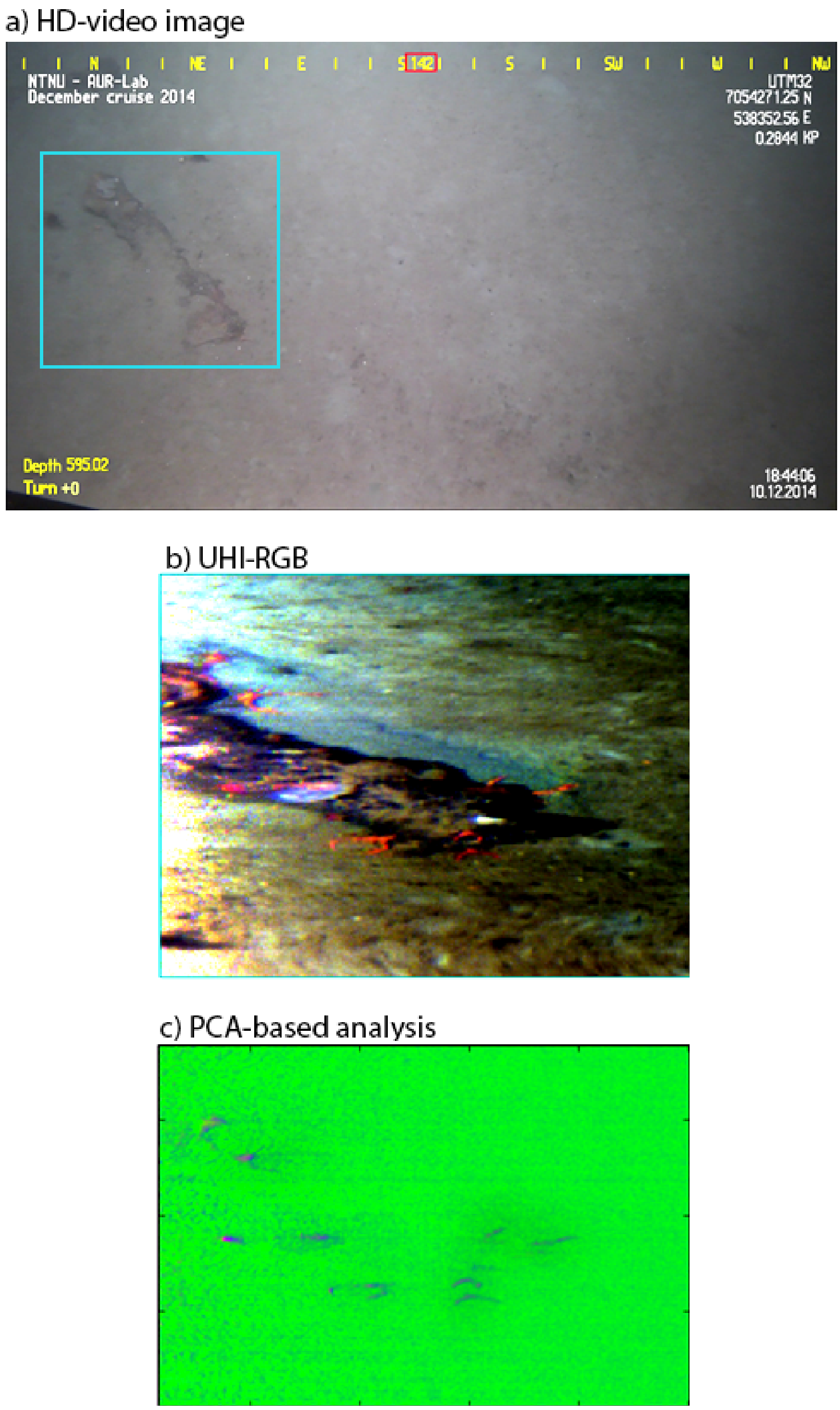

Figure 12. a) Video still of a manmade object with no reported OOI surrounding it in the log, b) UHI-RGB image showing at least nine squat lobsters on or around the object, c) image from Ecotone's software with three eigenvalues removed to highlight the squat lobsters.

Table 2 shows identification of a number of species and their coverage for the major classes based on pixel count following classification in ENVI. The entire spectral library was used for classification of the lawnmower box transect, and the total coverage for the lawnmower box transect was 455m^2. Since there is still instances of classification contamination of similar spectra, the number of pixels cannot be used for counting the number of organisms at this time. The data is still included to give an impression of coverage, as larger organisms naturally will occupy more pixels. This issue remains a high priority for future development.

Table 2: Confirmed species list, identification success and coverage (from box transect) following ENVI classification. Sorted after abundance according to IMR's species list

Class	Coverage/455m^2	Identified by UHI	Notes
Cerianthidae (Tube anemone)	-	Partial.	Challenges in extracting spectral signature.
***Munida* (Squat Lobster)**	0.0194m^2	Yes	Good classification.
Sea Pen Pennatulacea (most likely *Kophobelemnon* sp.,)	-	Yes	Good identification of organism despite small size and top view.
***Bolocera* (Anemone)**	0.0962m^2	Yes	Very good identification of main body.
***Parastichopus* (Sea Cucumber)**	0.0094m^2	Yes	Good identification.
***Chimaera monstrosa* (Ghost Shark/Havmus)**	-	Yes	Only one appearance in UHI-data.
***Drifa* sp. (Cauliflower Coral)**	-	Yes	
Porifera (Yellow Sponge class)	0.0031m^2	Yes	Good identification
Pandalidae (Shrimp)	-	Yes	Distinct red color, but hard to confirm actual appearance due to size.
Brachyura (Crab)	-	Yes	Good identification.
Kelp (Algae)		Yes	Very good identification success. Detected in hard-to-see locations.
Axinellidae (Yellow/Orange sponge)	0.0107m^2	Yes	Good identification.

5.2 Geology

Automatic sediment analysis and classification procedures using UHI are under development in Ecotone. In the following section, these capabilities are demonstrated on a small scale using four Areas of Interest (AoI) from the dumping site selected by NGU (Figure 12). It is emphasized that the analysis tools will be developed for a larger scale in the near future.

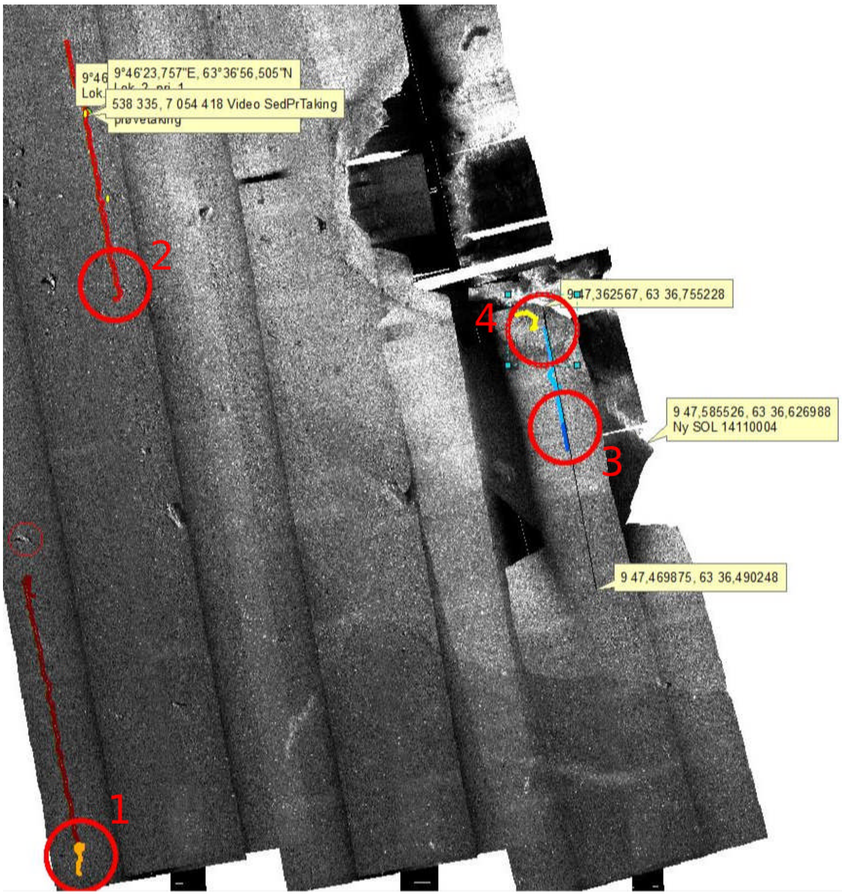

Figure 13. Sonar map (HiSAS from HUGIN 3000 AUV) HiSAS map with four specific areas of interest (AOI) located on the 3x500 m transect lines marked with red circles. This is the same area as in Figure 2.

200x200 pixels sub-images were extracted from the UHI-images for each AoI. Because AOI 4 appears to have a heterogeneous sediment composition, dominated by shells, the three first AOIs were analyzed first and used to illustrate the potential for sediment classification by UHI. Figure 13 shows from top to bottom the UHI-RGB-images of AOI 1-3. From the RGB images it is evident that AOI 3 has a much higher reflectance. By extracting three average reference reflectance spectra from the three areas this can be verified, see Figure 14. The three reference spectra looks by visual inspection very similar. By applying the selective principal component analysis (SPCA) described above, the components in the spectra representing the large degree of similarity can be subtracted. Figure 15. shows the reduced reference spectra.

By centering (removing offsets) and converting all spectra in the dataset to the same spectral components it can be verified that the method can give a well defined classification on the sediment type.

By calculating the correlation coefficient between the reference spectrum and every pixel in the UHI-images a measure of spectral separability can be obtained. Figure 2 shows the correlation coefficient between the reference spectra from AOIs 1 – 3 and the sub-images from each AOI. The RGB images from each AOI are included for reference. The correlation matrix is similar to a confusion matrix for classification. Reference Spectrum AOI1 correctly shows a high correlation (close to 1) with the UHI pixel information from AOI1, but that the spectrum is weakly (close to 0) or negatively correlated (<0) with the pixels from the other areas. Using Reference Spectrums AOI 2 and 3 also show a low or negative correlation with the other sub-images. The fact that reference spectra from the AOIs are strongly correlated with pixel information from their respective areas but have weak or partial correlations with other areas is strong statistical evidence for good discrimination between sediment types. An example of this is the spots in AOI2, which shows a strong correlation with Reference Spectrum AOI3. These patches of brighter sediment are often found in association with the biofilm layer on the sediment, and is usually a result of a disturbance (e.g. a burrowing animal depositing fresh sediment, or other movement by benthic organisms).

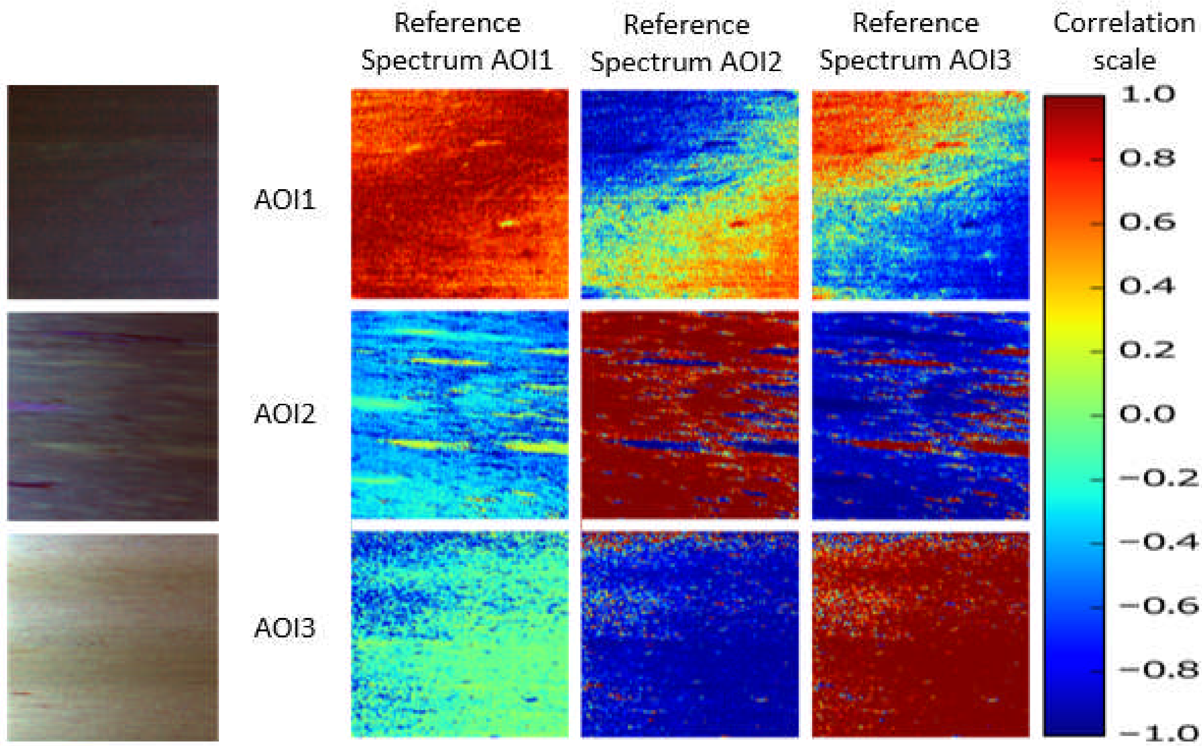

Figure 14. Color maps showing the correlation coefficient between AOI 1-3, using a Reference Spectrum from each AOI as a basis for each comparison. The subsamples consists of 200x200 pixels and represent approximately 20cm ground cover.

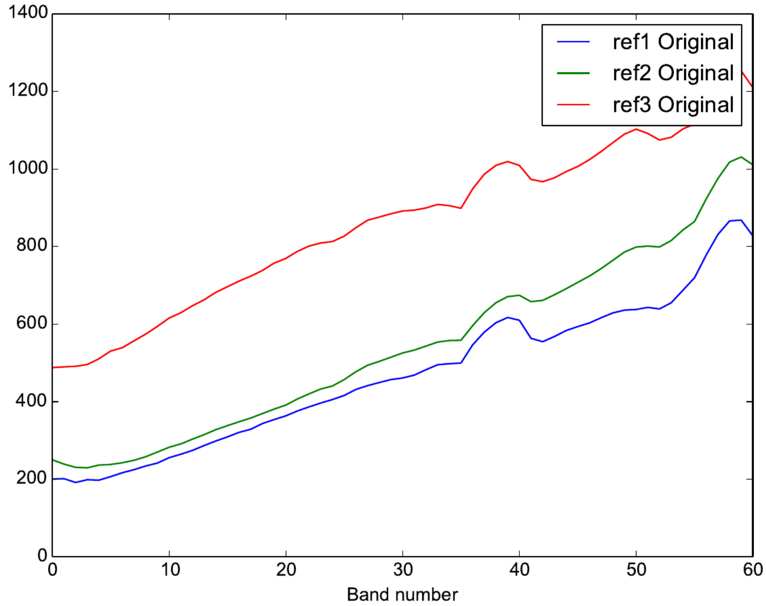

Figure 15. Reference reflectance spectra from AOI 1-3, shows that the shape of the spectra from the three areas looks similar.

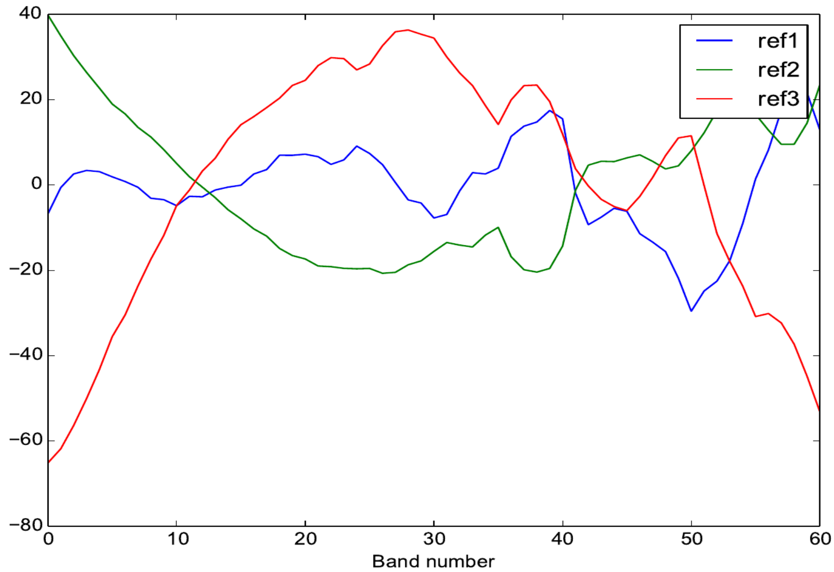

Figure 16. The reference reflectance spectra from AOI 1-3 reduced by SPCA.

Another way of visualizing the UHI discrimination is to plot every sample (pixel) in a scatter plot, where the X and Y-axes are projections along two selected spectral components. Figure 17 shows an example where 200 random samples have been taken from each AOI. In this two-dimensional plane the samples from each AOI show a high degree of clustering and is therefore a parallel indication of the good discrimination between AOIs 1-3.

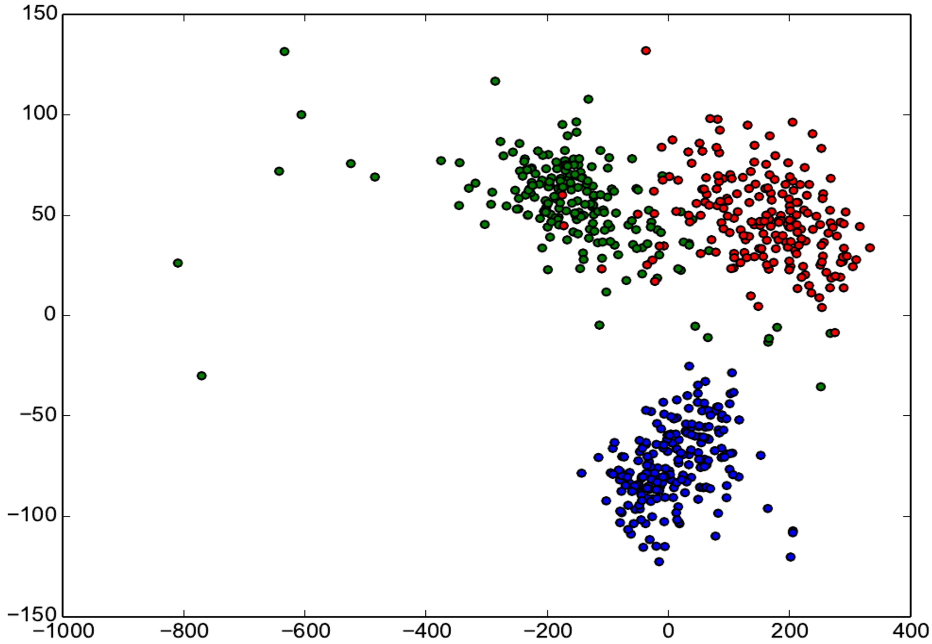

Figure 17. Scatter plot of 200 random samples from the three AOIs projected along two spectral components

In general, reference spectra of known OOIs are necessary to perform a good (supervised) classification. If a reflectance library of sediment types were available, a full classification with a probabilistic measure for the coverage/mixing ratio of sediment types would be feasible. As no such library for underwater characterization yet exists, following on from this study Ecotone can start building the library sample by sample. Methods can also be applied to make an automatic (unsupervised) classification. One method for splitting data into clusters with similar properties is the k-means algorithm. Using k-means, a reference library can made based on the Euclidean distance of components in the spectrum. User-specified limits are used to constrain the classification, with the result of added classes should objects not fall into the any of the existing.

Figure 17shows the results using k-means to identify classes across AOI 1-4. The unsupervised classification first groups the pixels into four classes using k-means classification, and adds new classes for pixels that do not fit into any of initial categories (total of seven). AOI 1 and 3 appears to be consist of mostly homogeneous sediment composition based on the proportion of pixel classification. A few pickets of other clusters are visible in AOI1, as well as the gradient between two similar classes, which most likely are due to uncorrected lighting differences (largest influence is the power surge from the ROV). AOI 2 and 4 have more heterogeneous compositions, with what appears to be shells and pockets of sand in between the undisturbed sediment.

The k-means method tells us that there is a significant difference in the spectra of these clusters. In order to assign a meaningful physical category to a specific object, further ground verification through sampling and several spectral measurements must be acquired in a controlled manner. This figure merely demonstrates the ability of the UHI to perform an unsupervised classification based on the spectral characteristics of selected areas on the seafloor.

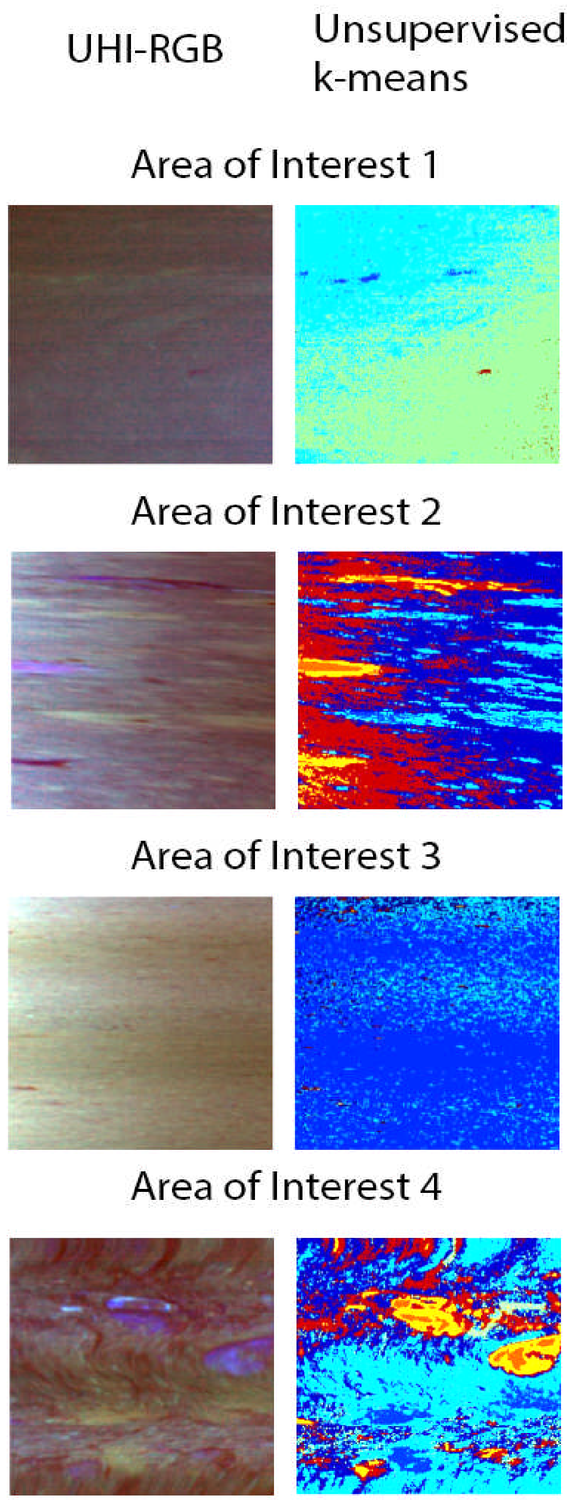

Figure 18. a) RGB images of AOI 1-4. b) K-means classification of AOI 1-4. Spectrally similar pixels are grouped together based on the Euclidian distance between the spectral signatures. A total of 7 classes were identified based on the input data, and at this point these represent clusters of pixels with spectral similarity and not a physical, classified object.

6. Discussion

6.1 Hardware and navigation logging

The UHI performed as expected with no technical issues. The transects were recorded as planned, and save for the aforementioned ROV-related disturbances, the operations went well. There were good communication between Ecotone and the ROV-pilots to ensure stable recording conditions. Both the ROV-pilots and NTNU’s DP-system worked as expected to provide as good recording conditions as possible for the UHI, as well as adjusting camera focus and position to provide optimal HD-video for the video loggers.
The ROV from NTNU received significant upgrades just before the start of the survey. This led to very limited time to test the integration of the UHI before leaving Trondheim harbor. Technical issues with the ROV also led to a one-day delay before the survey could commence.

The ROV experienced some operational challenges related to the depth and current conditions during the survey. There were occasions where the ROV was halted during the transects due to straying too far from R/V Gunnerus, which required the ROV to wait for the ship to catch up with the umbilical. In the extreme cases, the drag on the umbilical caused the ROV to be pulled suddenly back and upwards. As the UHI is a push-broom line imager, the movement of the ROV (in all directions) have an influence on the resulting image. Geocorrection will correct for the movement of the ROV and adjust the images accordingly, but only to the degree that the logging sensors can record. Sudden jolts, current influx and the subsequent counter-maneuvers have been known to be particularly challenging in the post-processing.

The box transect and Line 1 and 2 were mapped with little disturbance. As mentioned there were instances where current or umbilical drag caused sudden movements for the ROV, but these have been corrected for as best as possible. The transects on Line 3 suffered from stronger currents and increased drag on the umbilical for the flat part of the transect. As the incline of the seabed started to increase, eventually reaching the vertical coral wall it was not possible for the UHI to record coherent data due to being too far off the seabed. Since this survey, a frame for vertical mapping using UHI has been developed and successfully implemented on several occasions.

Challenges related to logging data and operating the ROV influenced the geocorrection of UHI-images. As it is a line-scanner recording between 20-50 frames per second, time synchronization and accurate navigation logs are necessary to produce optimal results. There was no time server on the survey, so the computers were synched manually. This appears to have had an effect on the overall image correction. The same can be said for the fact that the ROV often would swerve sideways, make sudden stops due to short umbilical or currents. When UHI-images appear skewed, it is most likely due to the ROV maneuvering back on track or at angle to counter the water masses or the short umbilical.

Developing the UHI system further is a top priority at Ecotone. This will be done by increasing the compatibility and flexibility of the system in order to allow easier integration on the main platforms used in underwater operations. Reducing the dependence on the ROV for navigation logging is an important step in this direction, and this will be done by integrating the appropriate sensors in the UHI system. This work is already underway, and it is expected that the next generation of UHI-units will have this capability.

6.2 Classification

6.2.1 Visual survey

The processing time added up to approximately 16 hours per transect. This includes the manual work needed in the classification process with angle adjustments and validation. At this point it was performed on a standard laptop with an i7 core. The development of the UHI software platform is expected to significantly reduce this processing time as most of the manual steps are automated. The scripting language used in ENVI is not optimal for large processing jobs of this size, and so the new platform will handle data much more efficiently.
The classification process returned results showing the ability of the UHI to locate and classify objects based on reference spectra from a spectral library using ENVI. Larger objects such as anemones and sea cucumbers, of which there were many, are good examples of the classification process. Objects partially hidden or obscured outside the field of view of the video are also worth focusing on. Particular examples of this includes squat lobsters hiding under or behind objects, with their claws often being the only visible part.

Challenges with the classification process with were also highlighted. The current process is based on the core functionality of the ENVI platform. This project has shown that new methodology will have to be developed to improve the classification process when working with only the visible part of the light spectrum. This is particularly true of the reference spectra, as the default SAM uses one spectrum for each class and does not feature any variability for the spectral signature. Thus, when the pixels in an image is projected in the n-D space during classification, there is only one strict reference vector to which the unknown pixel can be compared. This issue has a top priority, and will be addressed in the software platform developed at Ecotone.

Larger objects are initially easier to classify correctly than smaller objects. This is showcased with objects such as anemones, sea cucumbers and algae. Part of the reason is that it is easier to extract spectral signatures from larger objects, as a larger surface area will yield more pixels to use as a source. With the above-mentioned limitation of SAM in mind, the higher success rate with larger objects makes sense.

We also observed some class contamination between visually similar objects. This occurs when visually and spectrally similar objects fall into different classes depending on the stringency of the spectral angle used. A larger spectral angle will include a larger number of pixels (and thus more objects), but may overlap with other similar classes and thus “overtake” the other class. Another issue with increasing the spectral angle is that more pixels may be classified into a class they do not belong to. This can happen on different (but similar) objects, but also on the same object. An example of this is when an anemone’s center is perfectly classified, whereas the tentacles are not. These issues all point to a need for improved algorithms for separating spectrally similar signatures. We have already shown some of the development in this area in the sediment comparison section, and this will be an integral part of the upcoming software platform.

Area coverage were calculated using pixel coverage at Due to the aforementioned challenges with class contamination, it is not possible to use this particular classification set from ENVI for feature counting. This also goes for post-classification cleaning of uncertain pixels. At this moment, it is only possible to do this on a per-scene basis, and thus there is not enough control over the accuracy yet. Both of these issues are expected to be solved shortly in the internal software development, where the algorithms will be made to work specifically for UHI. The existing methods (in ENVI) are made for data sets on completely different scales.

There is not a 1:1 relationship between the species detected by UHI and seen on video. This is due to the camera pointing forward at an angle, while the UHI is pointed straight down. This gives the camera a wider field of view than the UHI. Still, the video log provided by IMR was very helpful in validating our classifications. It also helped us identify some of the more challenging organisms, such as less visually distinct corals and sponges.

A series of scripts developed especially for UHI were introduced after the initial ENVI processing. In the end, they will be one of the core modules of the software platform that is under development, but we were able to use them as standalone routines to explore the data from the survey. For now they are simple enough to properly process excerpts from the data, but will soon be modified to process entire transects. The main advantage of the method used in the scripts is the ability to manipulate the UHI-data. One can enhance and detect smaller and visually hard to detect objects by removing spectral components in the data. For example, the majority of the data in an image scene will most likely be sediment. Thus, by removing the first spectral component, and second if needed, a large bulk of unneeded data is removed. The result is that other spectrally distinct objects are visually enhanced as their spectral components are emphasized.

We have also shown examples of how the high spectral resolution of the UHI-data can be used for emphasizing OOI that are rare or invisible to standard optics. As shown in Figure 11, none of the lobsters colonizing the manmade object are recorded in the video log. UHI-analysis revealed at least nine squat lobsters on or around the object. One of the main advantages of a hyperspectral image is that images can be visualized using different wavelengths. So instead of the normal red-green-blue combination, colors and features can be enhanced by an alternative combination of color bands. In this case, the lobsters are enhanced removing the spectral components of the background (which constitutes the majority of the data in the image), and thus their claws and carapace becomes much more visible.

6.2.2 Sediment

The correlation analysis of the spectral data of the sediments in area 1-3 in Figure 12 shows that the UHI technology is capable of separating between sediment types even difficult to discriminate on video. With the automatic classification using the k-means algorithm it is clear that classes can efficiently be separated and identified. As it was not the scope of this survey to take several sediment samples in these areas it is difficult to verify the method and results. However in a recent project UHI sediment classification and grab samples were compared with a high degree of agreement (more details in next section).

Using the UHI as an optical non contact and objective underwater sediment classification method seems feasible in the near future. The main limitations are to get verified spectral fingerprints of sediments and the relatively expensive computational calculations necessary.

7. Future works

7.1 Mapping of drill cuttings

Mapping the extent of sediment deposition following a drilling event is an important part in assessing the impact of the operation. This is done not only immediately following the event, but also later to assess the rate of recovery. It is challenging to visually discriminate between the layers of thin particles that make up the drill cuttings and the sand in the sediment, especially in the transition zones. Therefore, grab samples are taken to analyze the faunal and chemical composition of the seafloor.

To illustrate the UHI systems future capabilities for sediment classification, we will give an example from another project. We wanted to test the UHI's ability to discriminate between areas with different concentrations of drill cuttings (with increasing distance from the drill site). Together with Akvaplan niva and ENI Norge as part of Petromaks 2 Joint Industry project. The grab sample sites at 30m, 60m and 125m distance from the drill site were compared using the sediment comparison tool described in the previous section.

The results from the northern line showed that Grab Site 1 (30m) was markedly different from Grab Site 2 (60m) and 3 (125m). The figures in the left "Correlation"-column in Figure 20 shows the three sites as compared to Reference Spectra 1 (from Grab Site 1), where Grab Site 2 and 3 are markedly different. This is consistent with the visual survey results as concluded by our partner. The grab samples further solidified the UHI's results, as they also indicated that Grab Site 1 was different from the two others (Figure 20; Unpublished material courtesy of Akvaplan niva / ENI Norge). The grab samples also suggested, based on the faunal composition, that Grab Site 2 and 3 were very similar. The UHI also reached the same conclusion when using Reference Spectra 2 (from Grab Site 2) (right "Correlation"-column, Figure 20). Thus, the UHI, visual survey analysis and grab samples all reached the same conclusion. The transition zone for sediment deposition following the drilling event is somewhere between 30 and 60m, and this is consistent with the initial hypothesis following the visual survey.

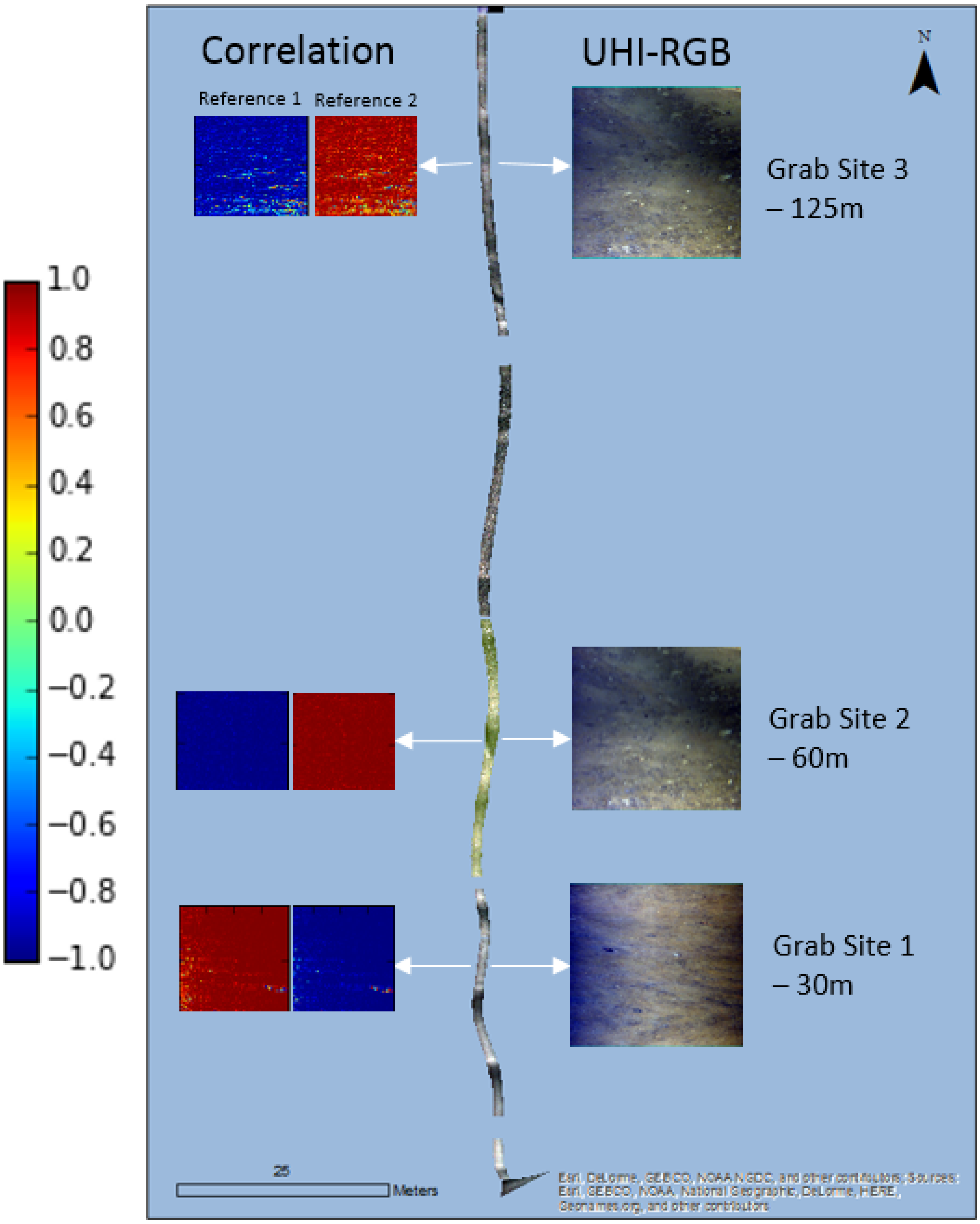

Figure 19. Spectral comparison of the top layer sediment at the first three grab sites, using Grab Site 1 and 2 as separate references (Reference 1 and Reference 2, respectively. Reference 1 shows that the top layer sediment at Grab Site 1 is markedly different from Grab Site 2 and 3. Reference 2 shows that Grab Site 2 and 3 are very similar to each other. This corresponds well to the macrofaunal analysis performed using grab samples. (Petromaks 2 Project. ENI Norge/BARCUT)

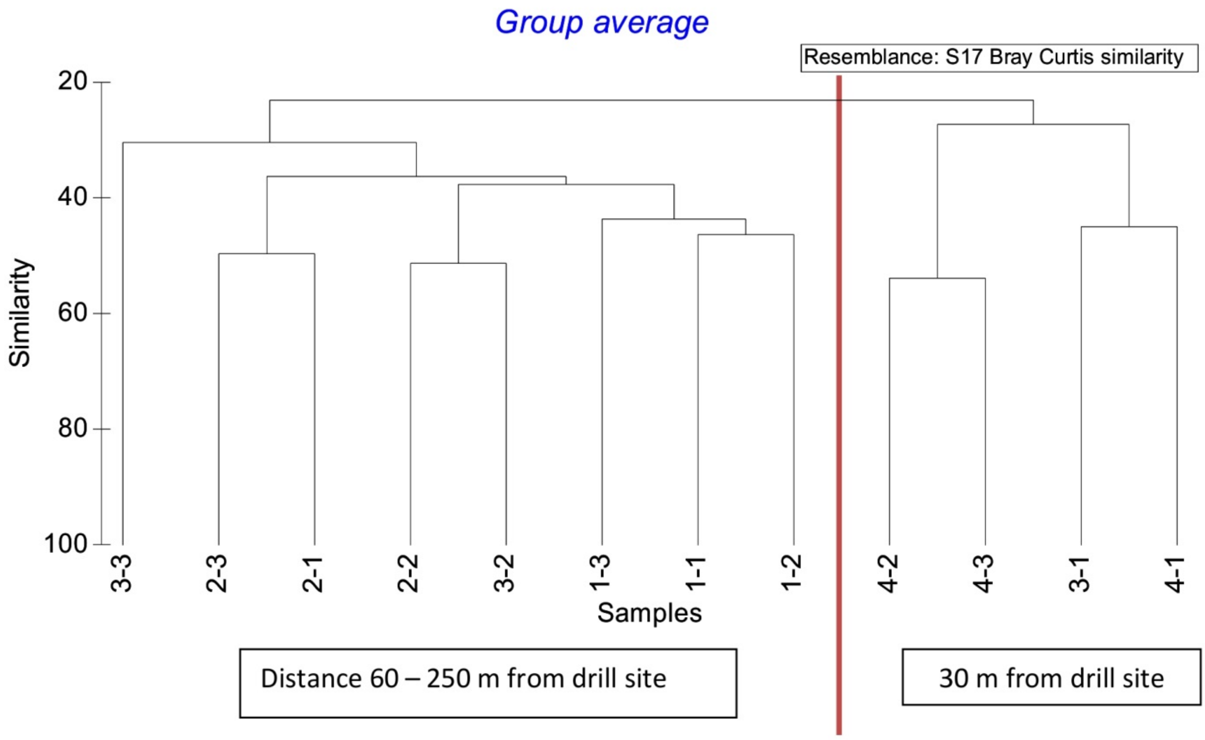

Figure 20. Similarity matrix calculated from the macrofaunal data, clearly showing that the sampling station closest to the drill site (30 m) differed from the remaining stations. The remaining stations were not markedly different from each other. The preliminary hypothesis is that the "recovery zone" at this site is between 30 and 60 m from the drilling site. Data courtesy of Akvaplan niva / ENI Norge

7.2 Hardware development

The development of an autonomous UHI-system is underway at Ecotone. The work is already underway in making the UHI a closed system, with data being processed and stored within the underwater housing. This will eliminate the need for transferring data via fiber optics, instead using the more common Ethernet protocol found on most ROVs. Processing data in this manner will also reduce the amount of data that needs to be transferred and the total size of the finished data set.

Ecotone also plans to integrate the UHI on an autonomous underwater vehicle (AUV). This work will start in the second half of 2015 with a first field trial planned in 2016. With the UHI running autonomously on an AUV, larger areas can be mapped in a shorter time than with ROV. It would also be possible to place the UHI on a tow fish.

Vertical mapping has been performed for the first time since this cruise. The UHI has been mounted on the ROV in a vertical position, and several surveys have been performed of vertical cold-water coral reefs at Haugbergneset in Balsfjorden outside Tromsø, and at Stokkbergneset in Trondheimsfjorden. The surveys so far have been successful in mapping near-shore hard-bottom fauna associated with the coral reefs, such as sponges, calcareous algae and colonial ascidians. These surveys were performed in connection with the Petromaks II research program.

7.3 Software development

Work on an independent software platform for Ecotone commenced already in fall 2014. The need to develop specialized software for processing of underwater hyperspectral images has been at the forefront of the company's software plans for a while. It has been important to make a streamlined, all-in-one solution for processing and classifying data, generating reports and visualizing images without needing to rework existing software where the main support and development libraries are for in-air or air-to-water use. The first version of the platform was released for internal testing in June 2015.

The main part of the software is the underlying processing engine. It consists of several modules that will handle the different tasks as they are called in the processing workflow. An early version of the GUI is shown in Figure 22. The streamlined workflow will import data as produced by the UHI and generate the result, be it a report or a digital map with vector graphics and area coverage for each class. The engine has received particular attention in order to handle the amount of data that can come from the UHI, in order to process it automatically and perform the tasks requested by the user. This is the core of the Data Management module, which will handle import and export of data and the internal data flow. This is essentially the part that replaces the ENVI part of the file management, as we have the ability to import and export files readable by other software. This is important to ensure compatibility with different sensors on the import side, and other post-analysis and GIS-tools on the export side.

Figure 21. An early version of the Graphical User Interface of the Ecotone software platform, with the Spectral Library module open. The toolbar give access to various tools and settings for the workflow, including project management, data management and analysis

The Analysis module will handle the spectral analysis in the software. It consists of selected algorithms and classification methods modified for automatic processing. One example is *Belief propagation*, a Bayesian network model. To simplify the process: the pixels in an image are hierarchically clustered according spectral separability, i.e. how closely they resemble one another. The algorithm will focus on achieving the least amount of spectral variability within a group cluster compared to the other clusters in the image. An unknown object will compared to the already assembled clusters and matched to the most spectrally similar. The Spectral Library module is then queried with the signature and matched to a local entry in the database. If one does not exist, there will be an option to create one. This module contains all spectral data, along with associated metadata about the entries in the database.

8. Conclusion

Through this project, we have:

- Demonstrated the technical robustness of the UHI as a part of the ROV sensor suite for the duration of the survey, with no UHI-related setbacks.
- Demonstrated the ability of the UHI to create GIS-compatible maps using UHI-data with both RGB and classified images.
- Demonstrated the ability of the UHI to record data in parallel with a standard visual survey
- Demonstrated the ability of the UHI-data reveal otherwise invisible information from the seabed through data analysis. Many OOI require a trained eye to be detected on video, while the UHI has the ability to detect even the smallest and most obscure OOI in its field of view.
- Demonstrated the potential of the UHI as a tool for automatic sediment classification.
- Mapped out the areas of improvement for the UHI-system, with top priorities including integrated sensor logging and improvements of the spectral analysis workflow.

This project has been valuable for the development of the UHI methods, both as a tool for seabed mapping but also as an analysis tool. The size of the dataset is the largest processed to date, and has highlighted challenges with the data processing and classification to be solved in the near future. Cutting edge software part of the software platform development at Ecotone were used in showcasing the ability of the UHI to extract and visualize data invisible to the naked eye. Through the development of the methodologies, writing the report and processing data, many lessons have been learned that will serve to focus the development of the UHI on its key capabilities.

The cooperation with the MAREANO program via NGU and IMR has been very important to the project. As professionals and potential end-users, NGU has provided constructive feedback on what they would like to see the UHI explore and questions they would like answered. IMR kindly provided a transcript of the video log taken in parallel with the UHI-recordings to assist with the classification and identification process. This cooperation has pinpointed key areas of the UHI-system for improvement in the coming times, and as a result, Ecotone will work to address all issues, concerns and suggestions based on the feedback from a valuable partner.

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APPENDIX 2

Spectral characteristics and inter-species consistency

NOTE: This supplementary note was provided by Ecotone, November 2015, after the main Ecotone report (Appendix 1) was complete.

Introduction

The spectral characteristics of biological organisms can vary with shape, size and position of the organism at the time of image capture. This influences the spectral signature acquired from the organism, and thus it is necessary to account for the variation of the signature within the spectral library.

The latest version of the Ecotone spectral analysis software includes the option to account for the variability in the spectral signatures. When plotting the spectra of individual specimens, the standard deviation of each band (wavelength) is displayed. This gives an indication of where in the electromagnetic spectrum the organisms shows variability and similarity.
The following figures displays examples of the spectral signatures and their measured spectral standard deviation, first with a focus on red objects and a final example of a coral.

Red objects

<u>Squat Lobster:</u>

Figure 1 shows the normalized spectral reflectance from five different specimens of squat lobster (*Munida*). There will always be some natural variation between the individual specimens as described above (size, position, shape), but the graph shows very similar signatures and overlapping standard deviations. Different amplitudes of certain spectral features (such as the one at ~690nm) may origin from different concentrations of the pigementation.

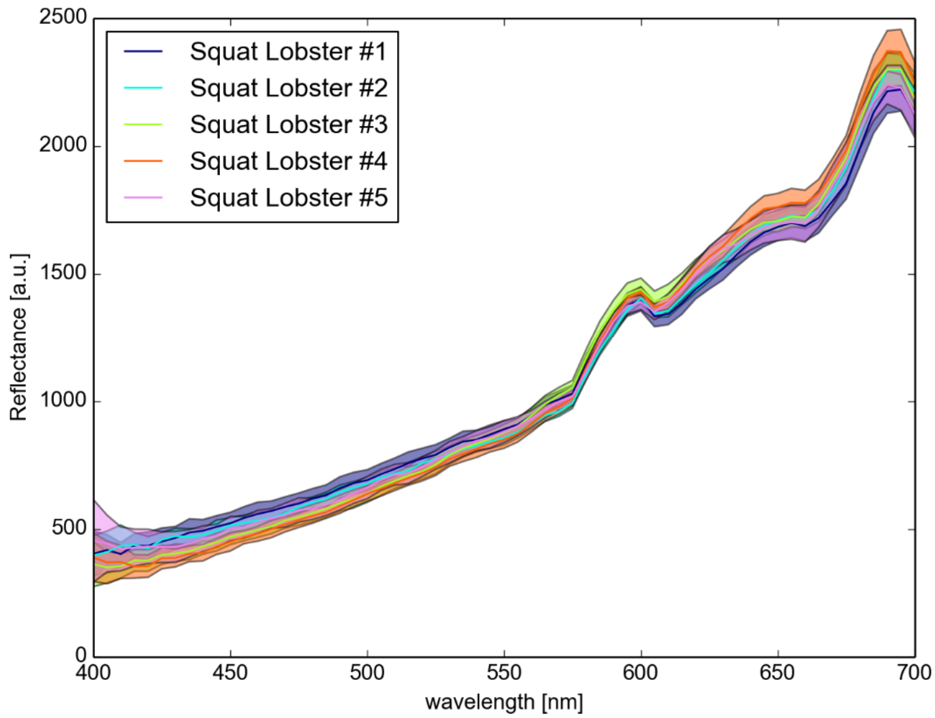

Figure 22. Spectral signature and standard deviation of five different specimens of squat lobster.

Tube Anemone

Figure 2 shows the normalized spectral reflectance from five different specimens of the tube anemone (*Cerinthidae)*. Despite appearing very dark (towards black) on both video and UHI-RGB, the spectral signature reveals a higher reflectance in the red part of the spectrum.

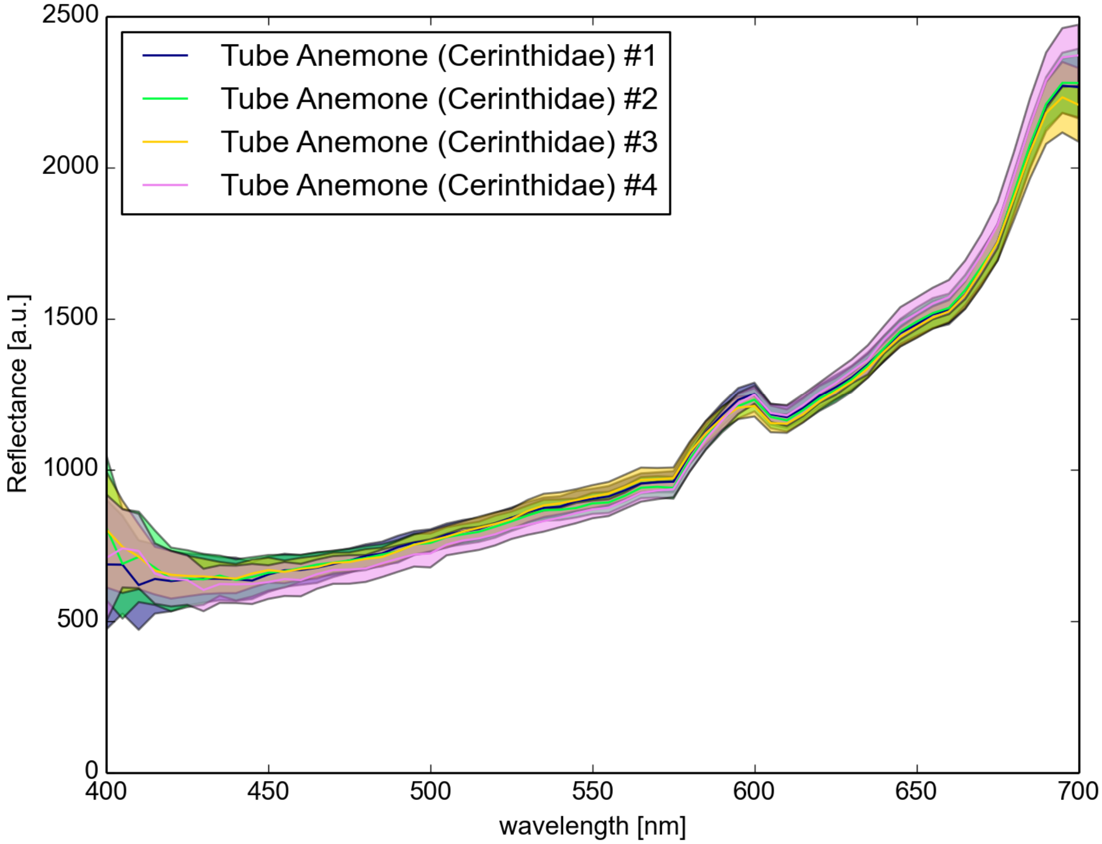

Figure 23. Spectral signature and standard deviation of four different specimens of the tube anemone (Cerinthidae)

Anemone

Figure 3 shows the normalized spectral reflectance from two different specimens of an anemone (*Bolocera*). These anemones are soft and the position of the tentacles are influences by the water activity, which can contribute to variability in the spectral signature. Nevertheless, both specimens show the characteristic absorbance feature at 640-650nm.

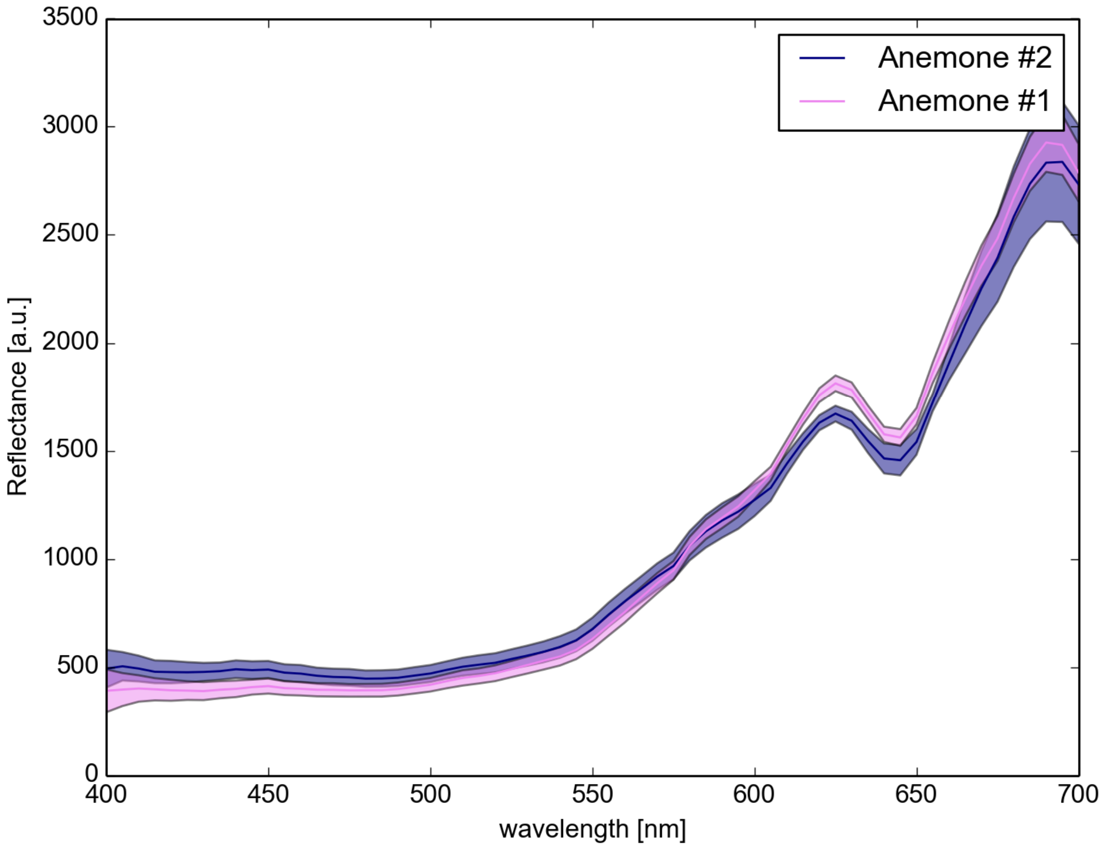

Figure 24. Spectral signature and standard deviation of two different specimens of the anemone Bolocera. The dip at 640-650nm is a characteristic absorbance feature of these anemones.

Sea Cucumber

Figure 4 shows the normalized spectral reflectance from two different specimens of sea cucumber (*Parastichopus*). The deep red color is evident in the graph, by observing the sharp rise after 550nm. Despite a difference at around 600nm, the main trend and absorption features are present in both spectral signatures. Sea cucumbers have generally been simple to classify, and this deep red signature contributes to that.

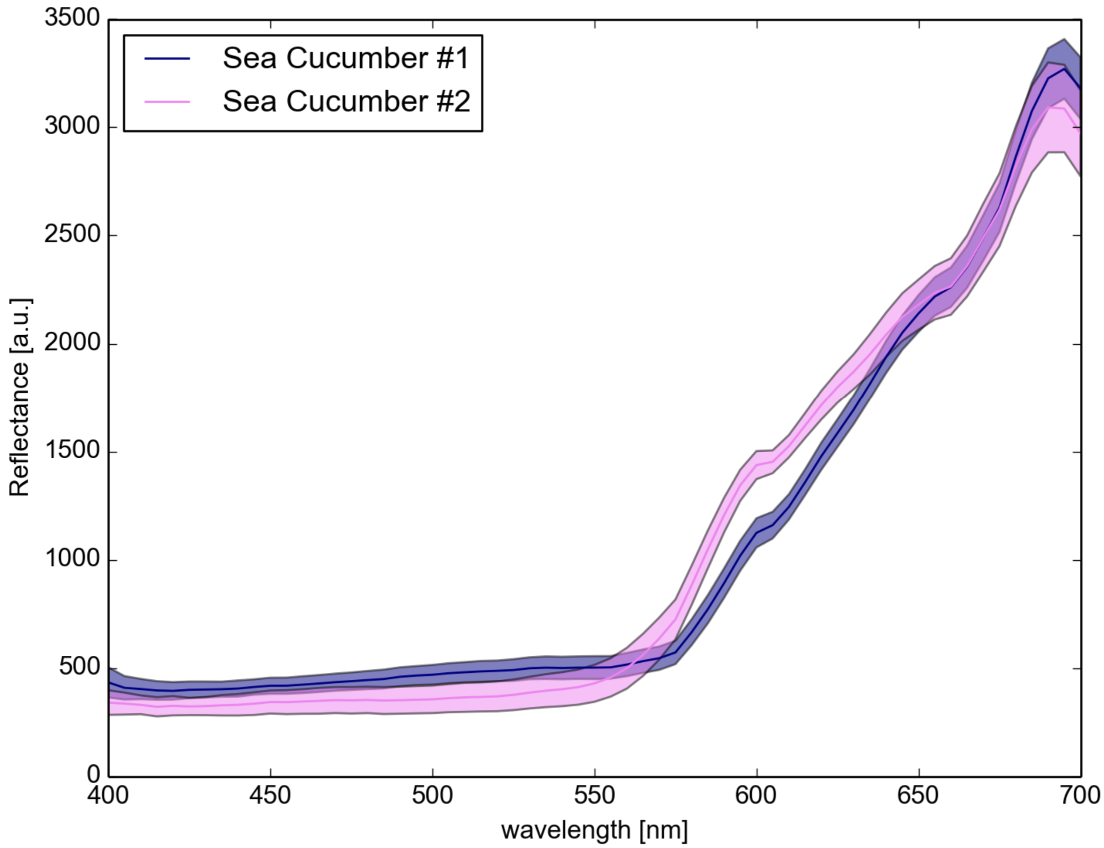

Figure 25. Spectral signature and standard deviation of two different specimens of the sea cucumber (Parastichopus). Both specimens show the same trend despite the gap at 600nm.

Comparison

Figure 5 shows mean normalized spectral reflectance of four red organisms described above. The graphs show the specific absorption and reflectance features of the different organisms which are used to distinguish them from eachother. The particular spectral position of the peaks are most interesting when distinguishing the different objects. One example is the Tube Anemone and the Squat Lobster which have in fact quite similar spectra, but where the highest peak around 700nm are shifted to longer wavelengths for the Tube Anemone making the classification stronger.

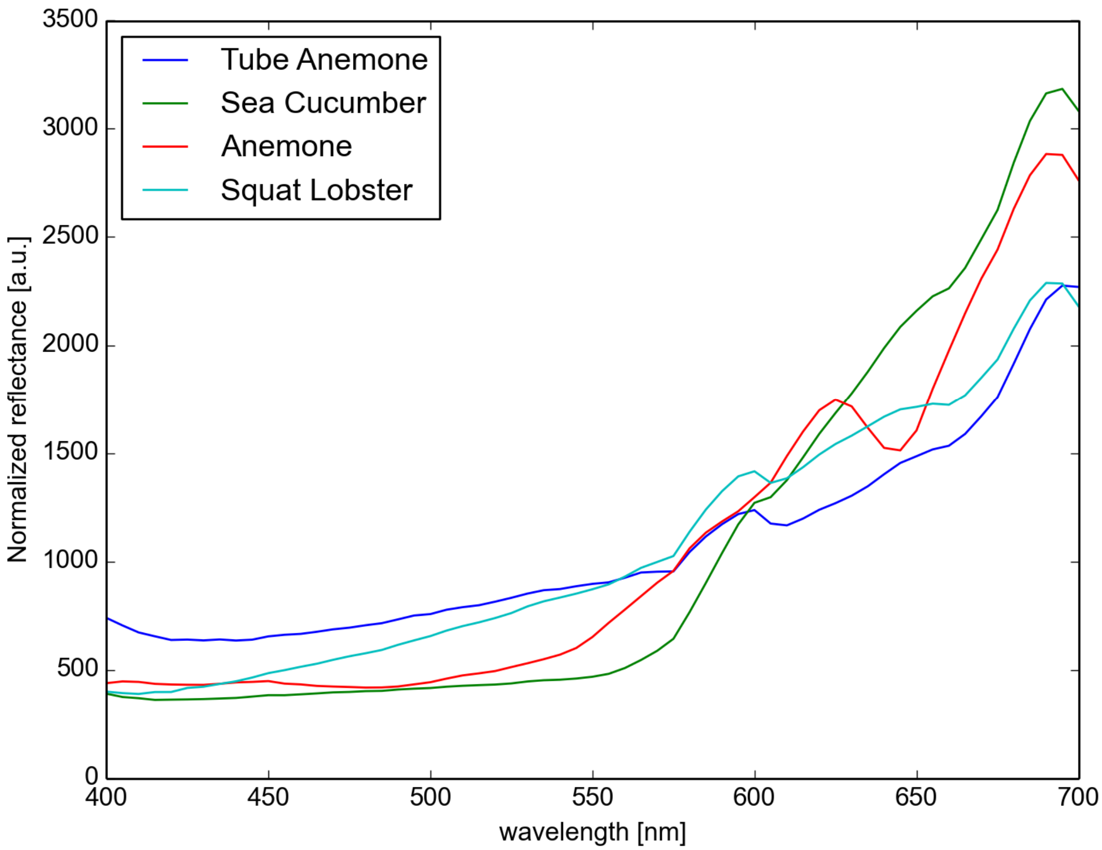

Figure 26. Comparison of the mean spectra from the four different red objects (Tube Anemone, Sea Cucumber, Anemone and Squat Lobster).

Coral

Paramuricea

Figure 5 shows the normalized spectral reflectance from three specimens of the coral *Paramuricea*. All three specimens show some different amplitudes at approx. 680nm. The overall shape is however the same. This is good as the coral has a highly variable morphology, but according to our analysis, the spectral signature remains similar between the specimens, and the spectral features remains on the same wavelengths.

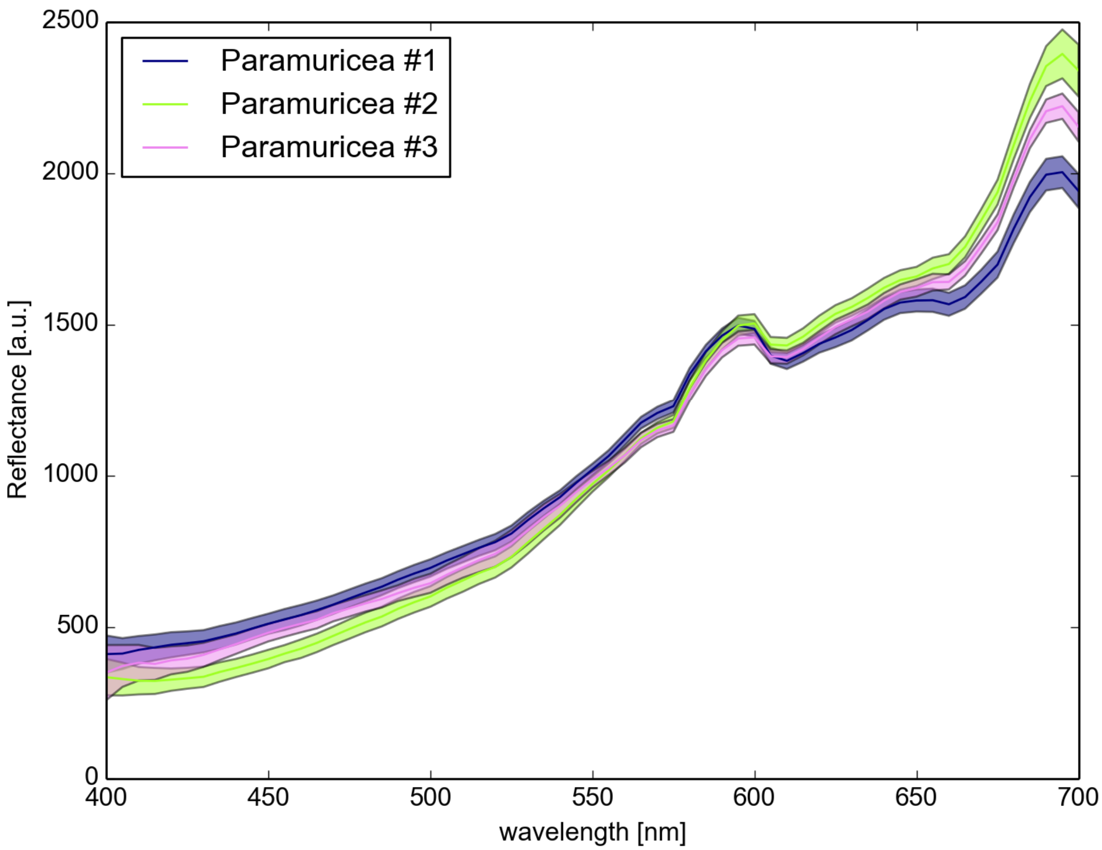

Figure 27. Spectral signature and standard deviation of three different specimens of the coral Paramuricea.

Future development

These examples are created with the newly released beta-version of the Ecotone spectral analysis tool. The platform already performs classification and geocorrection independent of the ENVI software previously used. This platform will be further developed and extended during the rest of 2015 and H1 2016, with a significant focus on classification algorithms to improve the spectral identification methods.

GEOLOGICAL
SURVEY OF
NORWAY
- NGU -

Geological Survey of Norway
PO Box 6315, Sluppen
N-7491 Trondheim, Norway

Visitor address
Leiv Eirikssons vei 39
7040 Trondheim

Tel (+ 47) 73 90 40 00
E-mail ngu@ngu.no
Web www.ngu.no/en-gb/