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Extraction and synthesis of environmental information from multi-source data

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Contents

1. Introduction

The effect of environmental variability and consequences of abrupt change can have severe effects on citizens' working and living conditions. For instance, an oil spill caused by a tanker accident in a vulnerable coastal zone area can result in irreparable damage, if not detected in time to conduct effective countermeasures. Likewise, rapid changes in sea ice conditions can lead to delays in ship traffic, or even to accidents, which in turn may lead to marine pollution, expensive rescue operations or loss of human life. Avoiding such events, or at least reducing their negative effect, has a high priority in governmental organisations and industry. However, efficient information systems for obtaining the required information in time are not always available.

Users need reliable data sources and means to obtain the desired, key environmental parameters in a timely manner. In addition to a suitable infrastructure, consisting of facilities for data acquisition and management, efficient analysis tools for classification of the current environmental state as well as change detection algorithms, must be in place. Development of computer systems often demands large resources, especially in terms of manpower and time. Building subsystems and single tools that can be reused in different application domains is thus a sound approach to cost reduction. Moreover, better estimates of important environmental parameters can be expected, since quality controlled algorithms are applied, rather than developing new ones from scratch.

The overall objective of the FET-ENVIS project has been to develop and evaluate computer methods that have a potential for application within a wide range of environmental problems. The underlying algorithms were developed for efficient extraction and synthesis of environmental information using multi-source data. Measurements from satellite Earth Observation (EO), airborne and in situ systems are combined to get a better estimate of environmental parameters. Existing satellite systems provide valuable information for large areas, which can be difficult or expensive to cover by traditional data collection campaigns. Unfortunately, the currently operational satellites typically do not cover the users' area of interest frequently enough, or the remote sensing instruments are affected by meteorological conditions, such as presence of clouds. Complimenting EO data with airborne and in situ data, when available, will therefore maximise the basis on which decisions are made.

Using multi-temporal data is another technique for improving detection and classification algorithms. This approach has proven fruitful when analysing seasonal and other cyclic phenomena, such as crop growth, where time series of data for the same area can be used to fill in gaps in data coverage. Access to representative multi-temporal data is also crucial for change detection studies, enabling comparison of different scenarios for the same area at different times (e.g. "new" vs. "old", "current" vs. "normal" conditions).

In this 1-year assessment study we have investigated a suite of multi-source data analysis techniques and employed them in selected case studies, including cross-domain application of some methods. The concept of designing an environmental information system (EIS) by means of reusable analysis tools for different environmental problems is thereby demonstrated. On the other hand, it is clear that developing a full-fledged cross-domain EIS, will be a challenging task requiring multi-disciplinary expertise beyond that found in the current consortium. However, the FET-ENVIS project can be seen as a first step towards such a system, by demonstrating the feasibility of the overall concept and providing sample multi-source data algorithms and methods. Forming a wider consortium of e.g. the external experts participating in the method assessment workshop as well as other research institutes or commercial companies with expertise in software development, will be the next step ahead. After that, a project plan for EIS development will be defined and submitted for funding by interested parties in government and industry. Based on our experience from this and other projects, we estimate that a pilot or pre-operational EIS can be realized in 3-5 years, when provided with adequate resources for the amount and level of functionality demanded by the stakeholders.

The remainder of the report is organized as follows. Section 2 describes the multi-source data methods developed within the project and results from the selected case studies. This section also demonstrates the use of some of these methods in a new application domain. Next, we identify the general themes of our study and suggest potential benefits of the investigated multi-source data analysis methods in a wider environmental context. Here, we also draw upon input from the external experts consulted during the project and use this complementary information to define a set of high-level requirements for data and analysis capabilities in an environmental information system for monitoring and forecasting. Section 3 ends with an outline of a proposed continuation of the assessment project, based on the established combination of case study-specific and general aspects. Finally, we present the overall conclusions from the project, and make recommendations for future work in Section 4.

2. Case Studies

The case studies we dealt with during the 1-year assessment project were from both the terrestrial and the marine domain: crop classification and humanitarian operations on the terrestrial side and sea ice monitoring and oil spill detection on the marine side. These four case studies differ in many respects from each other: the size and nature of the objects to be observed, the spatial and temporal scale on which the objects change their dimensions and characteristics, the sensors with which the measurements are taken, the methods with which the data is analyzed and, most of all, what the results are needed for.

The following illustrates some of the differences between two of these case studies: oil spill detection and crop classification. The size and shape of oil spills on sea water change on a fast time scale and their initial position and movement is rather unpredictable, although areas of heavy ship traffic are more exposed than others and typical drift directions can be estimated from meteorological records. Apart from the type of amount of oil in the spill, the potential damage depends on if and where it hits the shoreline. Even discharges originating far out at sea can pose a risk to the coastal zone given certain wind and current conditions. This makes satellites applicable for monitoring larger areas to obtain a first warning of a potential spill, while aircraft surveys are more appropriate for more detailed detection and tracking. Once the amount and type of pollution has been verified, decisions can be made on whether immediate reaction is required to prevent further environmental damage. Therefore, algorithms for measurement and classification of oil spills from remote sensing and aircraft data must run in real time.

On the other hand, classification of crop by remote sensing methods constitutes a completely different situation. The location of the areas to observe is well known, and the fields do not change their size nor do they move. Furthermore, the time scale on which the observed objects change their characteristics is very slow compared to that of oil spills. Polar orbiting satellites with trajectories crossing the area on a regular basis are therefore an appropriate data source. Results from crop classification studies are not used for immediate reaction, but for long term planning purposes. Therefore, the algorithms for data fusion and crop classification do not have to run in real time.

The two other case studies lie somewhere between oil spill detection and crop classification, in terms of spatial scale and frequency of changes. Sea ice evolves on a somewhat slower time scale than oil spills, but nevertheless immediate reaction can be required, e.g. to warn endangered ships when an iceberg breaks off. Humanitarian operations, such as construction of a refugee camp, require environmental data that change on slow time scales (as for crop classification). However, rapid reactions are required if, for instance, an unexpected growth of the number of refugees occurs.

In this project we have identified three basic parameters that can be used to categorize the four selected case studies: (1) the time scale on which the observed objects change, (2) the spatial scale on which variations occur and (3) the required temporal scale of the whole investigation cycle from detection to decision. These parameters have strong implications on which algorithms are suitable for analysis and classification, and on which sensors can be used to provide input data with the required spatial and temporal scale. With respect to these three parameters, the four case studies are rather different and ensure, therefore, that the results from our assessment study have general implications for other environmental applications as well. This is particularly important for the investigation of the cross-domain applications that we will address in Section 2.5 and for the extrapolation of project results to a wider environmental field, which will be the topic of Section 3.

In the following, we describe the four case studies in more detail, including tests of cross-domain application of some of the algorithms originally developed for one particular case study. The presentation focus on the results obtained in each case, while a description of the algorithms themselves can be found in the project Review Phase Report (Deliverable D2).

2.1 Sea Ice Monitoring

2.1.1 Background

Synthetic aperture radar (SAR) obtains images of the Earth's surface independently of light and cloud conditions. High spatial resolution and a large volume of information on sea surface and ice properties contained in SAR images make them valuable in many practical applications such as navigation, fishery, and development of oil and gas fields on the Arctic shelf.

Up until the mid-90s satellite high resolution SAR was only available for narrow swaths, typically in the order of 100 km or less. However, with the launch of the Canadian RADARSAT-1 satellite in 1995, this situation changed. The wide spatial coverage of the RADARSAT SAR with 500 km wide swaths, makes it useful for global scale sea ice monitoring, and its data can be combined with other active and passive microwave data to improve the temporal coverage. RADARSAT SAR data also enable assessment of sea ice parameters for large areas with a much higher spatial resolution than the data source traditionally used for this purpose (SSM/I) can provide.

In literature, a number of algorithms have been proposed for sea ice classification. For instance, some algorithms rely on look-up tables that are based on extensive field measurements (Onstott et al., 1979). These algorithms only consider each pixel separately and do not take into account values or statistics of the surrounding pixels. To remedy this shortcoming, many mehods have used various statistical and/or texture parameters to distinguish between different ice classes (see e.g. Kwok et al. (1992, 1995); Wohl (1995); Lyden et al. (1984); Shokr (1991); Soh and Tsatsoulis (1999); Gill and Valeur (1999) and Sandven et al. (1999)).

Application of standard parametric statistical classificators is justified if the statistical distribution of the data is known. Unfortunately, this is usually not the case when a number of different data sources need to be fused in a sea ice classification algorithm. Input can be meteorological data, cartographic data in GIS format, passive microwave images and other data. In this work we have applied texture features derived from a Grey-Level Co-occurrence Matrix (GLCM) as well as local statistical features. As noted above, the investigated features cannot be assumed to follow a normal distribution, and this have to be taken into account when using statistical parameters in sea ice classification.

Neural Networks models are intensively studied in the last few decades and have been applied in a large number of remote sensing applications including classification of sea ice. The advantages of the neural networks are in their ability to incorporate in the classification procedure different types of data with different statistical distributions, provide non-linear discrimination between classes, and to better classify data degraded by noise (Atkinson and Tatnall, 1997). Examples of sea ice classification by means of neural networks have been reported in e.g. Bogdanov et al. (1999).

2.1.2 Methods applied

This study used the LDA (Least Discriminant Analysis) and BNN (Backpropagation Neural Network) algorithms applied and trained for sea ice classification problem using SAR images (Wackerman and Miller, 1996) and a (Bogdanov et al., 1999).

The LDA algorithm uses a set of texture parameters to distinguish between different ice classes, based on a set of training data provided by the operator. The process of construction of linear discriminants does not rely on any assumption of the form of probability density function and the estimation of its parameters, but uses instead the estimation of between and within class variability in the data set. The decision boundaries separating regions in feature space corresponding to sea ice types are hyper planes, and the performance of the algorithm depends to a large degree on the separation between clusters provided by the given set of texture and local statistical parameters. If the classes are well separated, the linear separation can produce satisfactory results. Non-linear separation may be required if the data clusters have a complex form and are interlocked. Multi-layer neural model with hidden layers is one of the methods that provide nonlinear discrimination between classes.

Our approach uses a fully connected, multi-layer, feed forward, backpropagation neural network (Bishop, 1995). The information propagates in one direction from input processing units to output processing units (Figure 1). Statistical and texture parameters from the SAR images are fed into the neural network. The input to a processing unit is the weighted sum of the outputs from the previous layer. During the iterative training procedure, the weights between processing units are adjusted. The result is a classification of each pixel, assigned a probability of inclusion in each class. The backpropagation neural network used for sea ice classification consists of four layers of processing units or nodes.

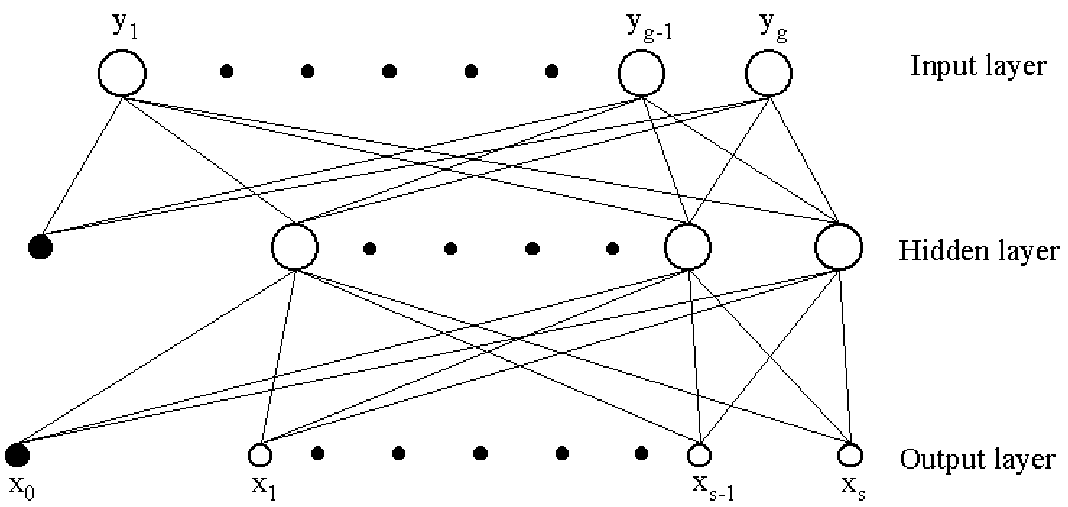


Figure 1 Network architecture.

2.1.3 Results from the Kara Sea

Test data were taken from an EU-funded project, ARCDEV (Pettersson et al., 1999), which conducted an expedition with icebreakers and a large tanker vessel through the Kara Sea area in April-May 1998. Figure 2 shows a map of the sailing route.

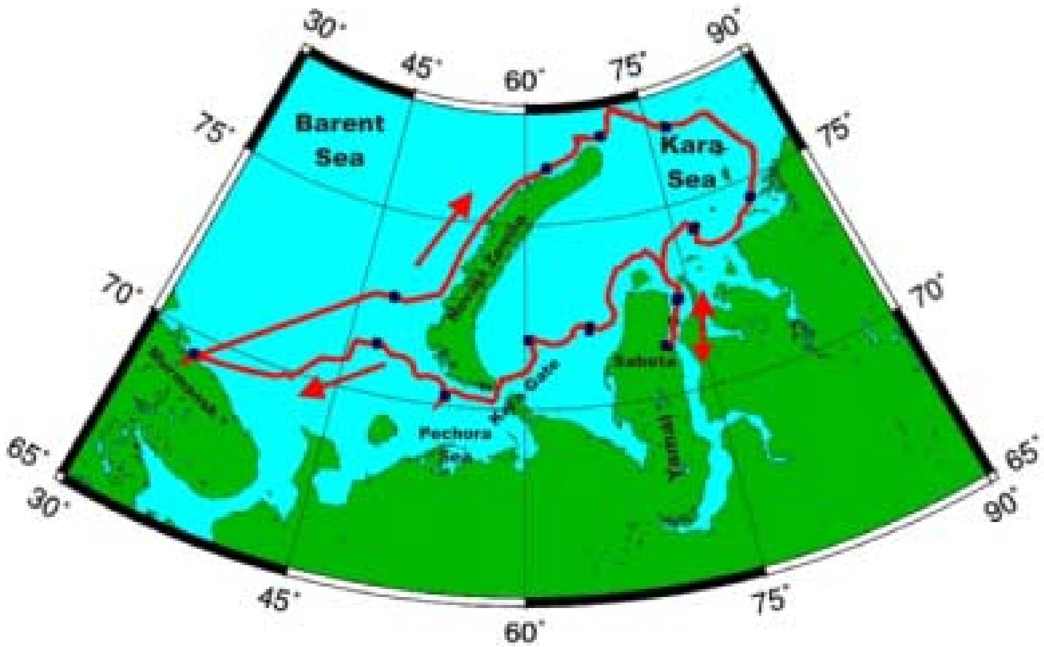


Figure 2 Map of the sailing route of M/T Uikku during the ArcDev'98 expedition (http://arcdev.neste.com).

Figure 3(a) shows a RADARSAT ScanSAR image acquired on April 30, 1998. The image covers the southern part of the Kara Sea, Ob and Enisey estuaries. The shoreline is marked by yellow on the image. The variety of different sea ice types and forms are presented on the image. In the central part of it, the areas of level fast ice have typically darker signatures than the areas of drifting ice in its upper part. The drifting ice consists mostly of deformed first-year ice and young ice. Open water and some new ice types were observed in the flaw polynias in the upper right-hand corner of the image.

The results of classification by LDA and NN algorithms are presented in Figure 3 (b) and (c), respectively. The visual analysis of the sea ice maps reveals that NN algorithm overestimates the young ice in upper left-hand corner of the image, where young ice exists in mixture with rough first-year ice. The NN algorithm, on the other hand, has an advantage of better classification of open water and new ice, which is evident in classification of flaw polynias in the upper right-hand corner of the image.

Separation of open water areas (low wind speed) and new ice (grease ice) from the surrounding ice is usually not difficult due to their low backscatter values and can be done by simple thresholding. In the selected SAR image some other sea ice types such as strips of small ice cakes exist, leading to variations of sigma zero values and thereby complicating the classification task. Application of texture and local statistical parameters with a neural network leads to better results in this case than using LDA algorithm with the same input parameters. The latter can be explained by better generalisation of the neural network on the data that the algorithm was not trained on.

The image was acquired nearly at the same time as the ship entered the area covered by the image so it was possible to identify sea ice types along the route very accurately. For quantitative assessment of the classification results homogeneous regions along the ship route were delineated and assigned manually to the sea ice classes according ship observations (test site 1). The comparison was done for the pixels falling inside those regions. Classification tables of the LDA and NN algorithm are shown in Table 1 and Table 2, respectively.

When assessing the presented results it should be taken into account that they are obtained using only one SAR image and therefore may not represent the overall performance of the algorithms when other geographical regions and seasons are considered. It also should be also mentioned here that sea ice conditions along the ship route are easiest for navigation and resemble those observed in the Marginal Ice Zone (MIZ). For automatic classification such regions represent more difficulties than the interior regions of sea ice massifs. The obtained results reflect "real life" results of automatic classification to be used for tactical navigation.

Application of the NN algorithm improved the classification accuracy of young ice by 42 % with a slight decrease in accuracy of classification of deformed first-year (FY) ice. Some image pixels were misclassified as level FY ice that was not observed in the testing region. Classification accuracy of open water (OW) and nilas class is low for both algorithms, but this can be improved by incorporating additional data sources such as radar data obtained at different polarisation and wavelength, passive and active microwave images.

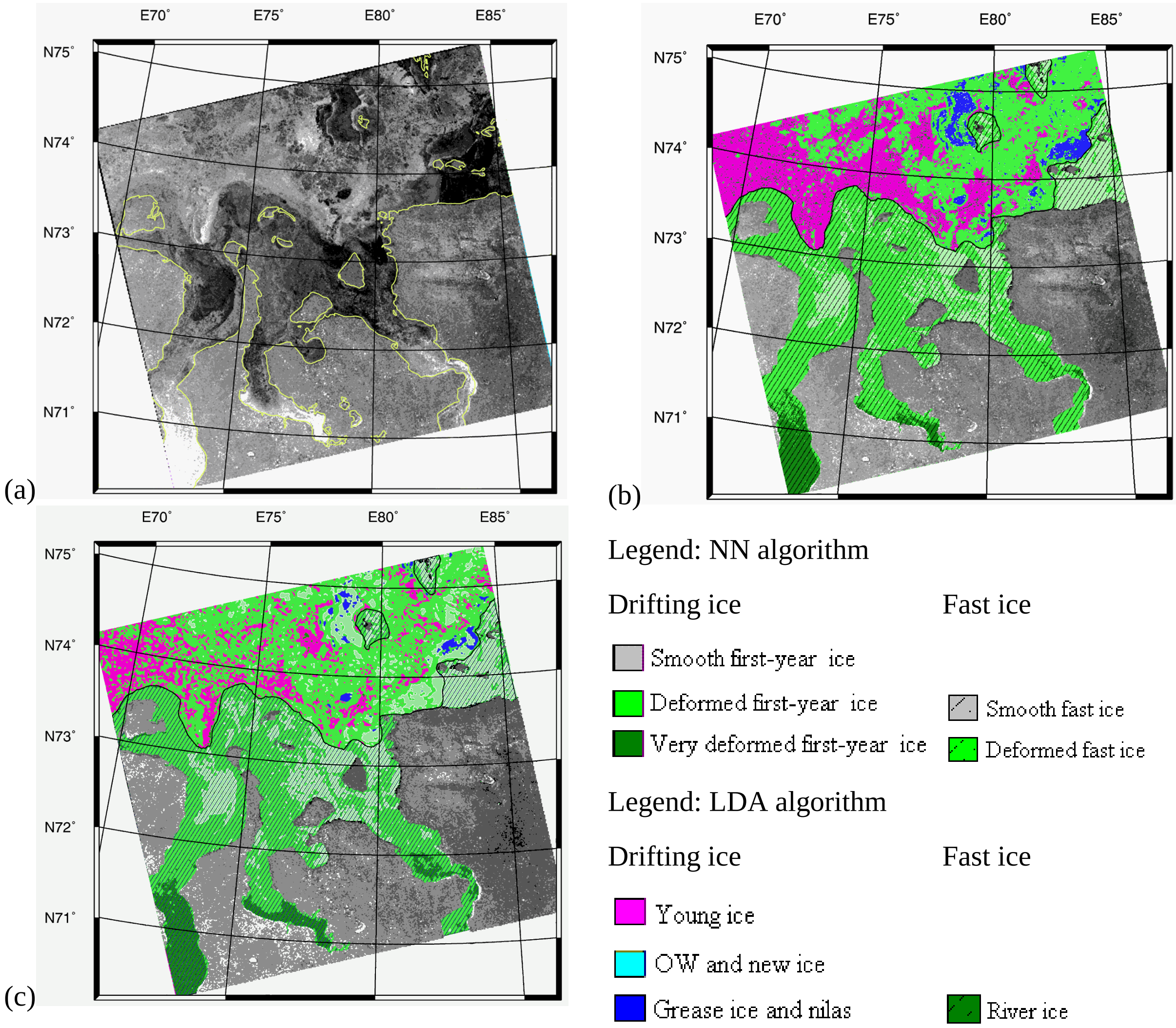


Figure 3 RADARSAT ScanSAR image (a) from 30 April 1998 classified with NN (b) and LDA (c) algorithm.

Table 1 Classification table for the LDA algorithm (test site 1).

	Number of pixels	Level FY ice (%)	Deformed FY ice (%)	Young ice (%)	OW and nilas (%)
Deformed FY ice	71 487	4	70	26	0
Young ice	41 619	2	59	39	0
OW and nilas	7 910	52	31	1	16

Table 2 Classification table for the NN algorithm (test site 1).

	Number of pixels	Level FY ice (%)	Deformed FY ice (%)	Young ice (%)	OW and nilas (%)
Deformed FY ice	71 487	0	65	35	0
Young ice	41 619	0	19	81	0
OW and nilas	7 910	4	59	12	25

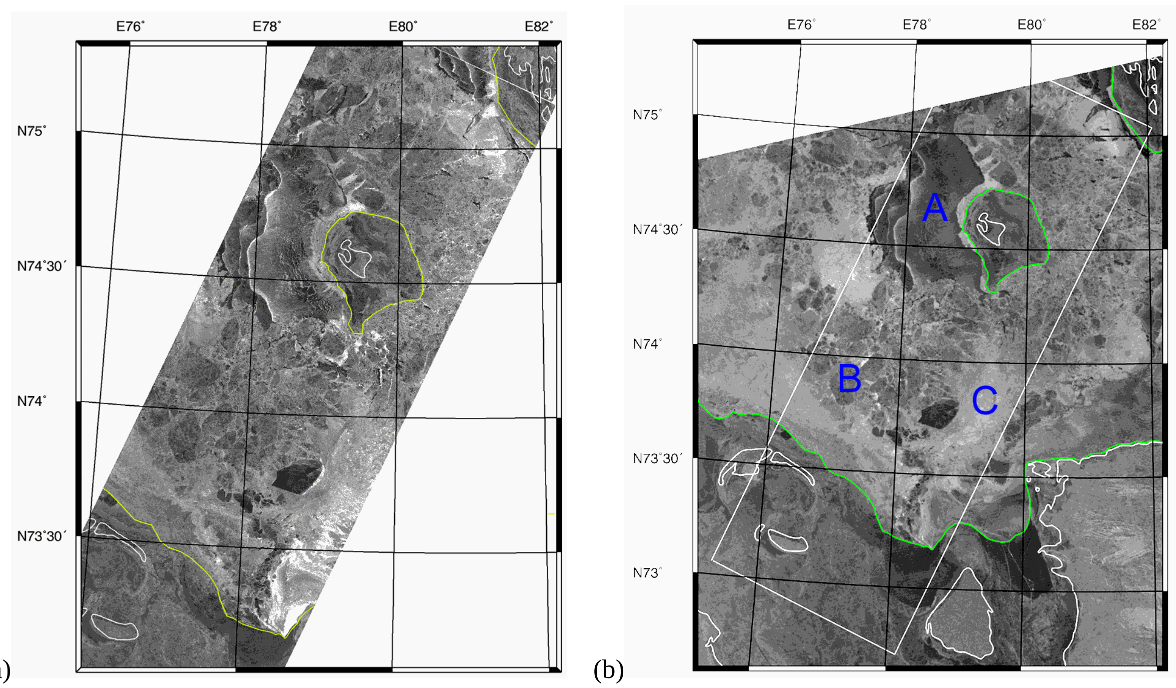
Three ERS-2 SAR images were acquired on April 30, 1998 near simultaneously with acquisition of the RADARSAT SAR image. The ERS-2 SAR images cover the same region (test site 2) as the fragment of the RADARSAT image (Figure 4). Both algorithms were applied separately to the ERS and RADARSAT SAR images to see the differences in algorithm performance entailed by the differences of radar parameters (polarisation, spatial resolution, range of incidence angles).

The quantitative comparison of the obtained sea ice maps was based on the results of manual interpretation by NERSC and NIERSC (Nansen International Environmental and Remote Sensing Centre) sea ice experts. The percentage of correctly classified pixels for each sea ice class is shown in Table 3 and Table 4 for RADARSAT and ERS SAR images, respectively. It can be seen that accuracy of LDA algorithm applied to the two different test sites is not very different (compare first row of Table 3 with diagonal elements of Table 1) while for the NN algorithm the discrepancies are quite big. The latter can be explained not only by the differences in sea ice conditions in two different test sites but also by two different approaches used for gaining truth data and subjectivity of the expert knowledge.

Analysis of Table 4 reveals that classification of young ice using ERS SAR images is better than using RADARSAT SAR images for both test sites. OW and nilas class is better recognized in RADARSAT SAR than in ERS SAR images. The neural network algorithm is also better at classifying OW and nilas in RADARSAT SAR images, for both test sites. These differences can be explained by differences of sigma zero values for different sea ice types at HH and VV polarisation and also by differences of texture features for different polarisations.

The conducted studies showed that application of the NN algorithm with texture and local statistical parameters improved the classification accuracy of young ice (5-42%) and OW (low wind speed)/nilas class (4-35%), while yielding a decrease in classification accuray of FY ice (5-11%) for different sensors and test sites. Application of the classification algorithms to the ERS and RADARSAT SAR images showed that classification accuracy of young ice is higher when ERS SAR images are used, while OW and nilas are better separated from the other sea ice types using RADARSAT SAR images. Merging of these two data sources in a single classification procedure based on NN algorithm is expected to improve sea ice classification results.

Texture and local statistical features applied in this study were found useful for sea ice discrimination. Especially for classes with overlapping ranges of backscatter coefficients, such as FY deformed ice and young ice. This experience will be drawn upon in a future sea ice classification algorithm.



(a) (b)

Figure 4 Mosaic of ERS-2 SAR images (a) and part of RADARSAT SAR image (b) acquired on 30 April, 1998, at 06:38GMT and 11:58GMT, respectively.

Table 3 Classification accuracy for RADARSAT SAR image (test site 2).

	Deformed FY ice	Young ice	OW & nilas
LDA	89.7	36.6	15.9
NN	83.3	63.3	50.8

Table 4 Classification accuracy for ERS SAR images (test site 2).

	Deformed FY ice	Young ice	OW & nilas
LDA	81.0	83.0	5.3
NN	70.3	83.0	8.9

2.2 Oil-spill Detection

2.2.1 Background and State-of-the-art

Multi-sensor fusion has been an active area of research for many years now, with publications from a number of application domains, including aerospace engineering, robotics and artificial intelligence. The aim of every fusion technique is to achieve improved accuracy and more specific inferences caused by the inherent redundancy provided by multiple sensors. A general overview about theoretical and application-oriented papers can be found in Varshney (1997) and Dasarathy (1998).

Multisensor environments typically generate a large amount of data based on sensors which often have different characteristics, gains, saturation levels and reliabilities. In addition, sensor data are often corrupted by a variety of errors and perturbations, which continuously vary because of temporal changes in the environment. Every sensor device has a limited accuracy while mapping a special aspect of the world and will, under some conditions, function incorrectly. To deal with these problems, many different specific fusion techniques have been developed using fuzzy logic, neural nets, expert systems and other approaches (Brooks and Iyengar, 1998).

Every technique needs a specific description of the problem to solve and the determination of particular parameters or rules. Up to now the lack of a generalized and unified representation of the information from multi-sensor input channels has been one of the major obstacles in implementing this technology. RUB has developed a general mathematical framework for the fusion of different kinds of information, and applied it successfully in several applications domains (see e.g. Steinhage et al., 1999; Steinhage and Winkel, 2000; 2001).

2.2.2 The sensor fusion algorithm

The Nonlinear Attractor Dynamics (NAD) algorithm is based on the mathematical theory of dynamical systems. Output values from several sensors are combined to obtain a non-linearly averaged estimate of the physical quantity to measure, and the NAD algorithm automatically discards outliers from the averaging process. The state of the dynamics represents the fused estimate of a physical entity. The estimate converges to the global stable state of the dynamical system.

By means of a unified way of representing information as stable states or *attractors* of a non-linear dynamical system it is possible to integrate different types of information such as expert knowledge, sensor information and information obtained from models seamlessly within the data fusion system. Figure 5 illustrates the concept of the NAD algorithm, where the overall estimate is a combination of the measured input values, but allowing different weighting to be associated with each input channel to cater for e.g. different confidence levels of the sensors used. Drifts within the time series of single sensors can be compensated for through a recalibration by the method of time scale inversion (Steinhage, 1999; Steinhage and Winkel, 2000). This is shown in the lower panel of Figure 5.

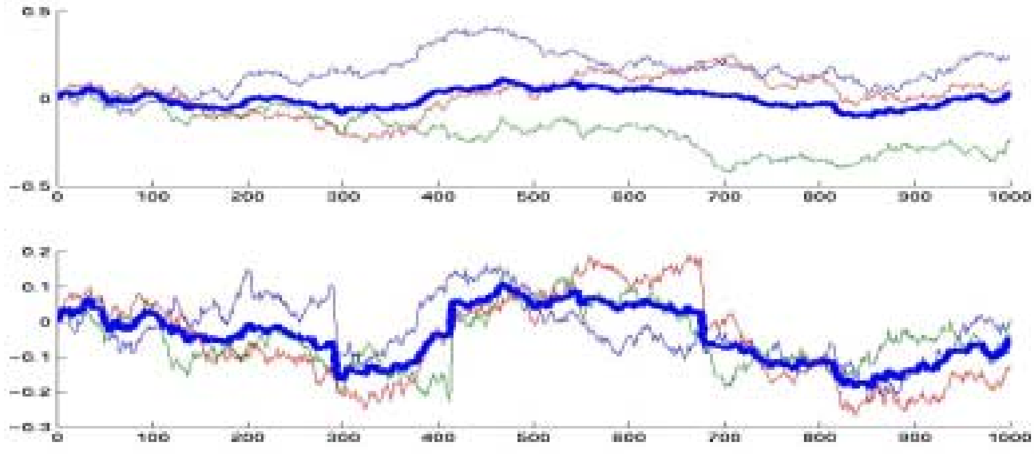


Figure 5 Upper panel: estimate (thick line) from three simulated sensor outputs (thin lines) over time. Lower panel: The same setup and sensor data but now with self-recalibration enabled (see text). Due to the recalibration, the variance in the lower plot is much smaller than without recalibration (note the different y-axis ranges).

2.2.3 Results

The NAD algorithm has been tested on a number of cases with simulated and real world data. We have verified the feasibility of our approach on the basis of simulated stochastic data sets (Figure 5) and on the basis of data from a study in which the brightness temperature of oil films on sea water has been measured. Figure 6 shows a simulation of five sensors each of which has a high noise component of 20% (stochastic and systematic errors). The time series required for the algorithm are obtained by scanning line by line the two-dimensional gaussian distribution. The arithmetic mean of the sensor outputs remains noisy while the dynamics extracts the original gaussian shape well.

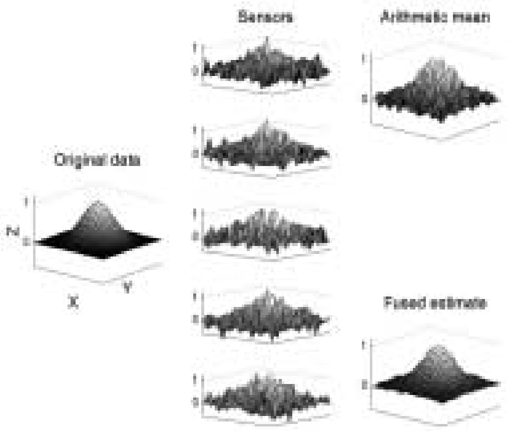


Figure 6 Estimation of a simulated gaussian distribution (left) scanned by five sensors (middle) each of which measures with 20% stochastic and 20% systematic error (offset). The right panel shows the linear average (top) and the estimate $m(t)$ (bottom).

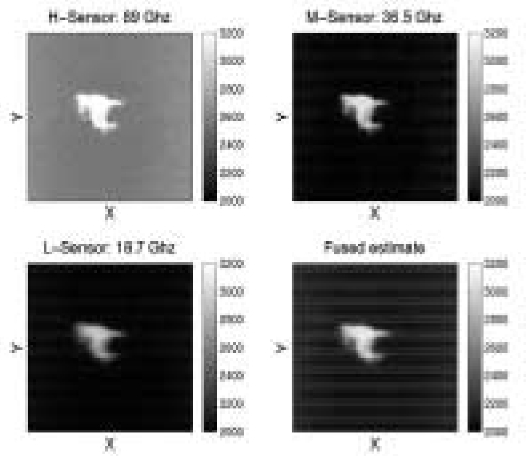


Figure 7 The lower right panel shows the result of a fusion of three temperature measurements (other three panels) obtained from airborne radiometers flying across an oil spot on sea water.

The NAD algorithm has also been tested with real sensor data from a remote sensing application. Figure 7 shows image plots of the raw output of three airborne microwave radiometers which measure the brightness temperature of radiation emitted and backscattered from an oil spot on sea water. The radiometers are tuned to three different frequencies of 89, 36.5 and 18.7 GHz, and scan the surface in lines from right to left using a parabolic reflector while flying across the oil spot. The lower right panel in Figure 7 shows the fused estimate of the temperatures, which was obtained by feeding the sensors' raw time series into the NAD algorithm. Although the upper left sensor has a strong offset and the lower left sensor has a very low resolution, the fused estimate shows a detailed brightness image of the oil spot. Taking the brightness temperature distribution as a basis for further analysis, other measures like the thickness and the consistency of the oil film can be derived.

These examples show how information from sensors and abstract sources (e.g. the recalibration information) can be represented by local attractors in a unified way. The method is specifically well suited for, but not restricted to, estimates of physical properties. By applying principles of dynamical systems' theory to the problem of self recalibration the efficiency and reliability of the estimates have been improved.

The NAD algorithm has been extended towards classification of sensor data. This will be described along with the investigation of cross-domain applications in Section 2.5.

2.3 Crop Classification

2.3.1 Background

Efficient environmental management practices require accurate and rapid information about land and ocean surface properties. Commonly, multispectral remotely sensed images are used to distinguish Earth surface feature on the basis of their spectral properties (Mather, 1999). Various forms of classification analysis can be used for this purpose. Traditional statistical classifiers, such as the maximum likelihood algorithm, have been used widely for several decades. However, there are certain problems associated with these techniques, including their assumptions that the data are normally distributed and that classes are mutually exclusive. More recently, alternative approaches have been developed which overcome some such problems. For instance, artificial neural networks, used increasingly in classification studies throughout the 1990s, have no requirement for normally distributed data (Kanellopoulos and Wilkinson, 1997). Additionally, unlike traditional ‘hard’ classification that represents features (e.g., pixels) according to mutually exclusive classes, fuzzy classification assigns classes on the basis of proportional membership. That is, while traditional hard classification associates each feature (e.g., pixel) with a single class, fuzzy classification associates each feature with several classes according to the proportion of the feature occupied by each class. This ‘fuzzy’ representation is more realistic of the continua of Earth surface features than hard classification (Foody, 1996).

Classification analysis involving single-date images has the drawback that, since maximum discrimination between different surface features often occurs at different times (e.g., the seasonal growth cycle of agricultural crops (Ortiz *et al*., 1997)), not all differences are incorporated in the procedure. Furthermore, since features are dynamic, it is often useful to observe their development over time (e.g., crop yield estimation). A solution is to use multitemporal images for environmental monitoring (Cherchali *et al*., 2000). For most current multitemporal classification techniques, a correspondence of time to growth state is established for each possible feature category that minimises the smallest difference between the given multispectral-multitemporal vector and the category mean vector indexed by growth state (Kimes *et al*., 1999). These techniques, however, are fairly inaccurate since only relatively few static spectral and temporal ‘snapshots’ contribute to feature identification. That is, images with specific spectral wavebands acquired on specific dates are used, rather than images with entire spectral and temporal continua. Using the latter may increase crop classification accuracy since they contain more information than the former (Lambin and Strahler 1994; Vieira *et al*., 2000). However, since any attempt to incorporate entire spectral and temporal continua in classification is likely to involve large volumes of data, the processing requirements for such procedures may be prohibitively high. One potential solution may be to use per-field classification instead of traditional per-pixel classification. Per-field classification, which associates feature classes with entire fields rather than individual pixels, may have considerably lower processing requirements than per-pixel classification (Mattikali *et al*., 1995; Aplin *et al*., 1999).

Generally, multispectral and multitemporal classification analysis has been performed using images from a single source. There are several drawbacks with single-source classification. First, this approach enables relatively limited feature differentiation. That is, different sources of imagery have different technical characteristics, enabling different levels of feature identification. Therefore, combining multiple sources can increase the amount of discriminating information in a dataset, compared to a single source (Solberg *et al*., 1996). For instance, the Landsat Thematic Mapper (TM) and Systeme Pour l'Observation de la Terre (SPOT) High Resolution Visible (HRV) satellite sensors have different spectral wavebands which, in combination, may generate more discriminating information than either source alone. Second, where multitemporal analysis is being performed, images at the appropriate timescale may be unavailable from a single source. A solution may be to combine images from different sources in multisource classification (Pohl and van Genderen, 1998; Vieira *et al*., 2000).

Methods for classifying agricultural crops using multispectral, multitemporal and multisource remotely sensed images were developed. A study area near Littleport, East Anglia, UK was selected for analysis, and optical Landsat TM and SPOT HRV images from 1994 were acquired. Initially, a per-pixel classification approach was implemented, by calculating the spatial-temporal response surface (STRS) for each pixel (Figure 8). Six crop classes were selected for analysis: fallow, onions, peas, potatoes, sugar beat and wheat.

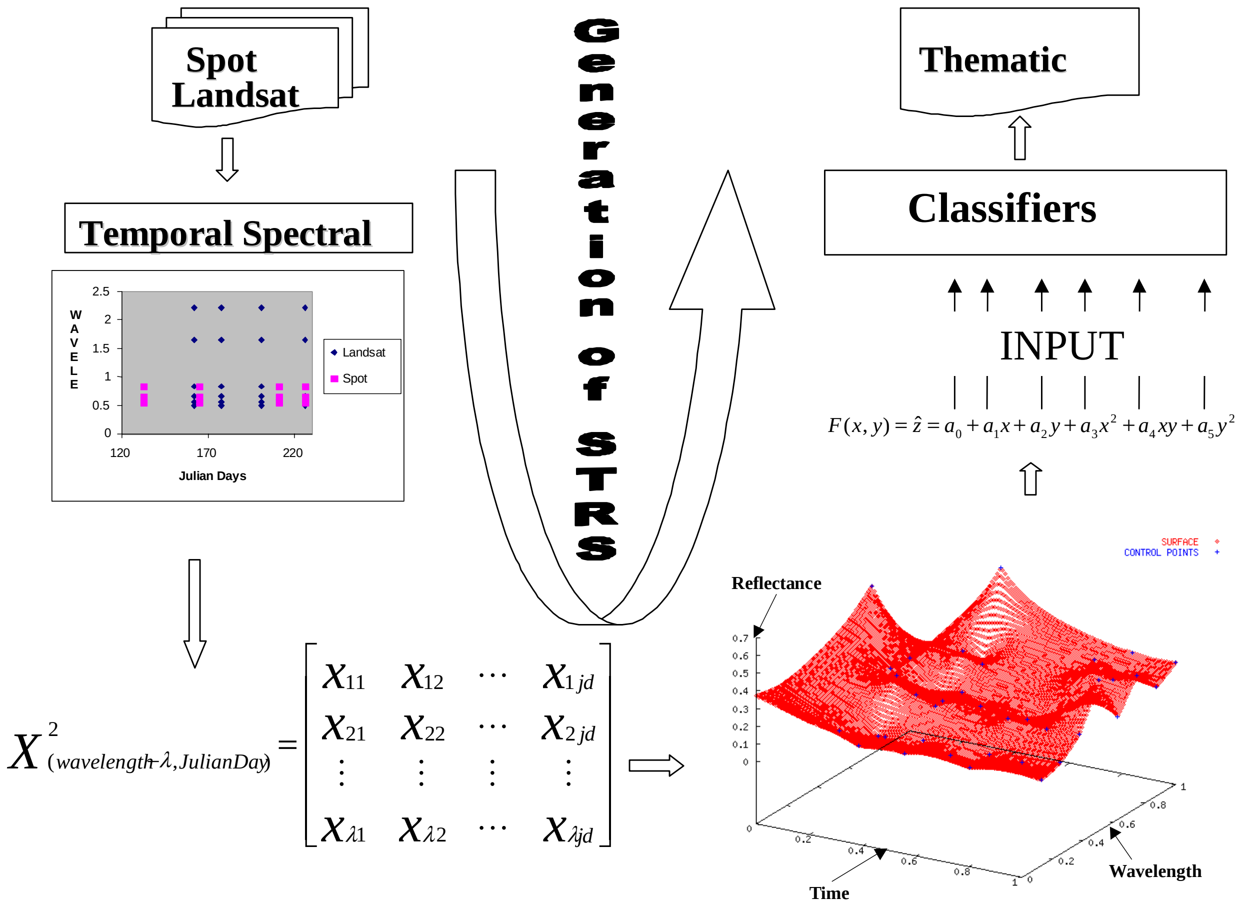
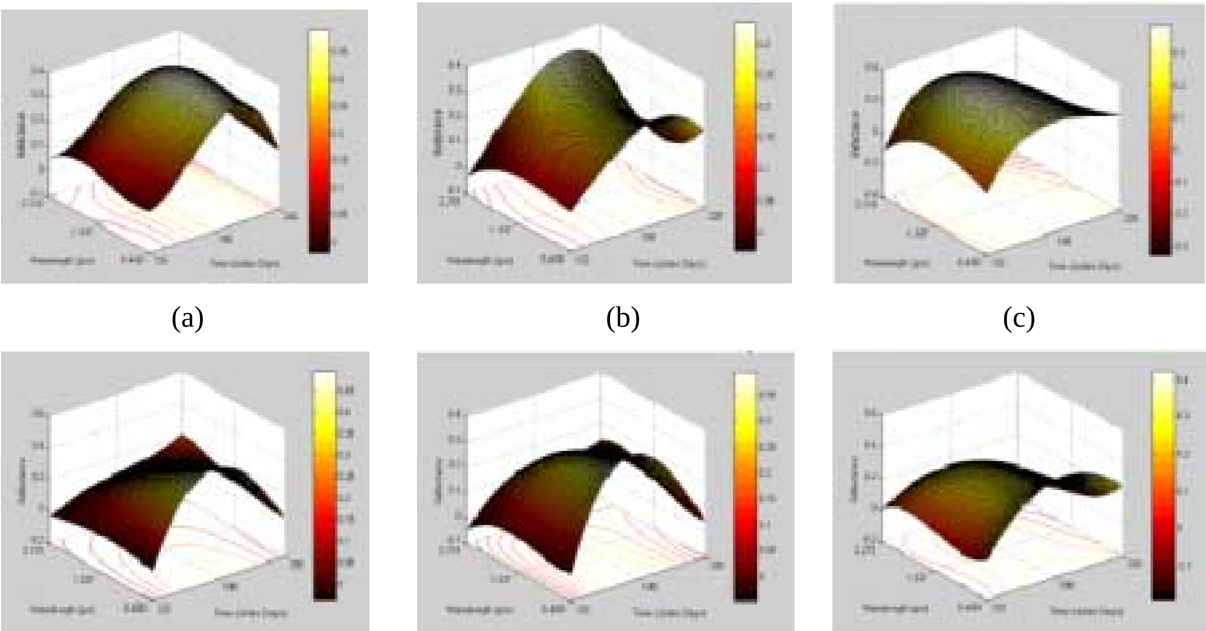


Figure 8 An outline of the procedure used to generate spatial-temporal response surfaces (STRS).

All pixels in the scene were characterised by considering their intensity values as a function of spectral waveband and time of imaging. For each pixel, an analytical surface was interpolated through irregularly spaced data points using bivariate interpolation methods (Figure 9). The analytical surface was parameterised by its coefficients, which were then input as discriminating variables to supervised classification algorithm such as maximum likelihood (ML) and artificial neural networks (ANN).

Each pixel was classified in this way, producing a per-pixel classification of the whole scene. Subsequently, a per-field classification approach was implemented, whereby analytical surfaces were interpolated for entire fields rather then individual pixels. For comparison with these two multitemporal classifications, traditional per-pixel ML classification was also performed using a single-date image.



(a) (b) (c)

(d) (e) (f)

Figure 9 Analytical polynomial trend surfaces and contours for pixels of (a) fallow, (b) onions, (c) peas, (d) potatoes, (e) sugar beat and (f) wheat.

2.3.2 Results

Overall classification accuracies, kappa coefficients and their variances are presented to indicate the accuracy of the three classification methods; and *Z* values are presented to indicate the significance of the classification accuracies (Table 5). Generally, the performance of the single-date classification (with an overall classification accuracy of 72.9%) was poorer than that of the two multitemporal classifications (both with an overall classification accuracy of over 84%). It is believed that this was due in part to the non-linear separability of the classes under study. Of the two multitemporal classification methods, the per-pixel approach was more accurate. For instance, the kappa coefficient of the per-pixel multitemporal classification was 0.848, considerably higher than that of the per-field multitemporal classification (0.688). A potential explanation for this may be that the relatively small training dataset used during per-field classification was inconsistent with the design properties and assumptions of the supervised ML algorithm.

The major diagonal *Z* value elements (representing the single error matrices) for the three classification methods were greater than the critical value (1.96 at a 95% confidence level), showing that each method was significantly more accurate than a random classification. Inter-comparison between the three methods (off diagonal *Z* value elements) indicated that, at a 95% confidence level, the performance of the single-date per-pixel classification was significantly less accurate than the multitemporal per-pixel classification ($Z = 7.57 > 1.96$), but not significantly different to the multitemporal per-field classification ($Z = 0.11 < 1.96$). There was no significant difference between the performance of the two multitemporal classification methods ($Z = 1.31 < 1.96$). It may be concluded from these findings that, overall, the multitemporal approach has the potential for more accurate crop discrimination than the single-date approach. However, when using ML as the decision rule for the multitemporal approach, it is important that the training dataset is representative.

Despite the relatively high accuracy of the multitemporal per-pixel classification, this method has the drawback that it requires lengthy processing procedures (Table 6). For instance, the total processing time of multitemporal per-pixel classification for a 285 pixel by 285 pixel image was over 10.5 hours. In contrast, for the same scene, multitemporal per-field classification took under 20 minutes and single-date per-pixel classification took slightly over 6 minutes. Clearly, the single-date approach is the fastest to implement. However, the significantly lower classification accuracy of this approach compared to the multitemporal approach may prohibit its use. Of the two multitemporal methods, although per-pixel classification was marginally more accurate and per-field classification employed relatively few training data (raising general concerns over the statistical validity of the results), the lengthy processing times of the former may be prohibitive. Instead, per-field classification may potentially provide equal or greater accuracy than its per-pixel equivalent (further analysis is required to verify this) with very considerable savings in terms of processing time.

Table 5 A comparison of accuracy measures for the three classification methods. *Z* values in bold typeface indicate significant improvements in the performance of the classifiers at a 95% confidence level (critical value = 1.96).

Accuracy measure		**Classification method**		
		Single-date per-pixel classification	Multitemporal per-pixel classification	Multitemporal per-field classification
Overall classification accuracy (%)		72.9	87.4	84.4
Kappa coefficient		0.675	0.848	0.688
Variance		0.000394	0.000129	0.01487
Z values	*Single-date per-pixel classification*	34.01		
	Multitemporal per-pixel classification	**7.57**	74.66	
	Multitemporal per-field classification	0.11	1.31	5.64

Table 6 Processing times for the three classification methods. (The CPU times listed are for a Sun Solaris dual-processor (450 MHz) with 18.2 Gb internal storage, 1000 RPM and a 1.6" UltraSCSI disk drive.)

Classification method	**Procedure processing time** (in seconds unless stated otherwise)				
	Pixel collection	File generation	Pre-processing	Classific-ation	Total *(Total in hrs:mins:secs)*
Single-date per-pixel classification	15.6	0	0	349.7	365.3 *(0:06:05)*
Multitemporal per-pixel classification	545	2364.1	32477.8	2509.9	37896.8 *(10:31:37)*
Multitemporal per-field classification	16.49	71.54	982.83	75.95	1146.81 *(0:19:07)*

2.4 Humanitarian Operations

Using interpreted objects in an IKONOS image, such as river areas, civil villages and major roads, together with a Digital Terrain Model (DTM), analysis of suitable camp location areas were performed in a GIS (Johannessen et al., 2001). The analysis is based on an IKONOS scene from May 2000, exploiting all four available bands. For a real-case computation of the best camp location many parameters have to be taken into account, sometimes also including political issues that that can be very difficult to parameterise. However, in this brief example for the Beldangi area in Nepal, only a subset of the environmental parameters of importance have been included:

- slope and aspect originating from the DEM
- distance to water, major roads and villages from the interpreted objects

The values and thresholds used are assumptions based on experience from the area. Additional information that would have been of interest include land use, water quality, bio-mass quality, population, ethnicity, temperature, prevailing wind direction, minimum area etc. Thresholds and rules for computing the best camp locations from the available data were as follows:

- Slope: < 7%
- Aspect: SW - S - SE
- Distance to water: 200-1500m
- Distance to major roads < 500m
- Not valid in existing civil villages

The result shows that the Beldangi I camp is partly settled in a none-suitable area. The reason for this is that part of the camp is closer to the river than the limit of 200m. In fact, there have been problems with water flooding in this camp, and embankments have been built in several places.

It should be noted that this is only a very brief example of a method that could be used for determining suitable areas. The limited data available and result shown in Figure 10 is neither sufficient for a quantitative assessment of a camp's location, nor must the result be seen as a criticism on where these camps have been located.

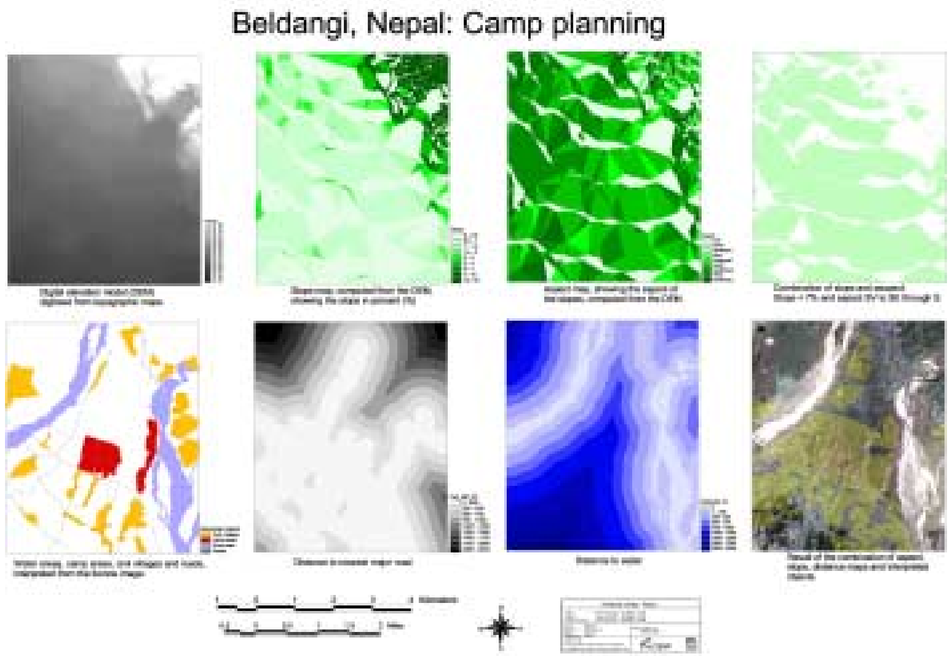


Figure 10 Result of the GIS analysis for finding optimal locations for refugee camps in Beldangi region, Nepal.

2.5 Investigation of Cross-domain Applications

2.5.1 Use of sensor fusion algorithm in sea ice classification

The NAD algorithm was tested on ERS-1 SAR image data obtained during a field experiment in the Barents Sea in March 1992.

The idea is to use the output of the NAD algorithm as input for a system of winner-takes-all dynamics in which different classes compete with each other. In this way, transitions between classes are brought about by bifurcations between stable states of a dynamical system. Based on an approach from the domain of autonomous robotics, where discrete behavioural states and the switching between them are expressed as bifurcating competitive dynamical systems (Steinhage and Schöner,1999), RUB has developed a dynamical classification mechanism.

In most cases, the problem of classification consists of the task to associate continuous subsymbolic sensor data with corresponding discrete symbols that characterise similarities or invariances within the sensor data. If the number of possible classes is lower than the number of bins the continuous sensor data are sampled with, the process of classification results in a reduction of information. Therefore, classification is advantageous if the class membership is the only relevant information in a particular application. Examples from the area of remote sensing are the problem of identifying crop types or the pollution of sea water from satellite images. Whenever the underlying sensor data are noisy, however, classification may be difficult: the sensor fusion algorithm has to decide whether strong variations within the data stream are just perturbations or class changes of the measured system. In remote sensing applications the systems to classify are mostly physical systems that change their states on slow temporal and large spatial scales only. This characteristic can be accounted for by representing the estimated class decision by a dynamic state variable within the classification algorithm. The sensor information is then used to modify this internal state dynamics rather than letting it directly determine the class. The advantage is that the dynamic properties of the underlying physical system can be mapped onto the time scale of the classification dynamics: changes in the sensor data stream are only interpreted as class transitions if they happen on the appropriate physical time scale; faster changes are considered as perturbations that do not affect the classification.

Because the dynamics acts on data provided in the form of time series, the spatial scale of the physical system has to be transformed into a temporal scale by scanning the images with a neighbourhood-preserving trajectory. Then the spatial areas can be classified from the image data.

Without changing the parameters of the dynamical systems, we have applied the classification algorithm to a different SAR-image of the same region (Figure 12). Like with the previous example in Figure 11, the ice types are classified very well. This underlines the robustness of the approach: without having to tune the class means or –widths again, the algorithm picks the correct classes.

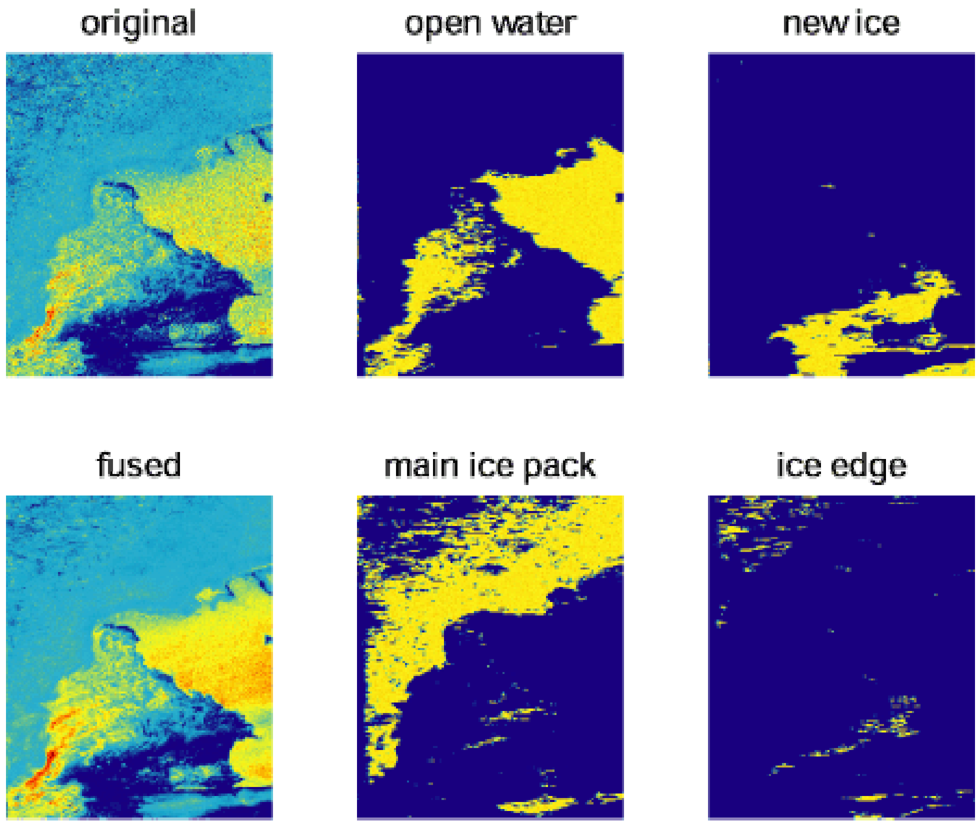


Figure 11 ERS-1 SAR image from 5 March 1992 and the classification made by RUB's sensor fusion algorithm (Steinhage and Winkel, 2001). Classes were defined by selecting mean backscatter values and widths for four characteristic regions: open water, main ice pack, new ice and the ice edge.

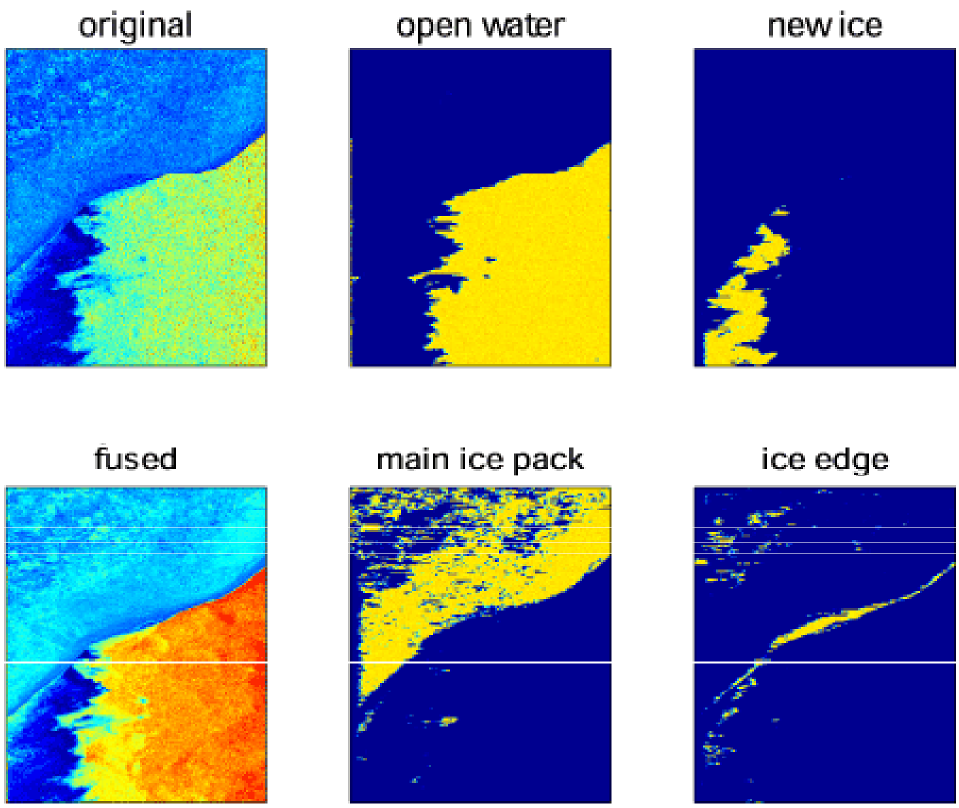


Figure 12 Another ERS-1 SAR image of the same region as in Figure 11 (original), processed image on the basis of neighbourhood preservation (fused) and the classification made by the NAD algorithm.

2.5.2 Comparison of three different sea ice classification algorithms

A classification by the three algorithms LDA (linear discriminant analysis), BNN (backpropagation neural network), and NAD (nonlinear attractor dynamics),applied to the same ERS-1 SAR image, are shown in Figure 13(b)-(d), respectively.

We only outline the main features of sea ice classification maps and describe how they change between different algorithms. The quantitative comparison of the classification results it is rather difficult because the algorithms were trained using different data sets and because different sea ice classes were selected for subsequent classification in the case of the NAD algorithm.

ERS-1 SAR images of the Marginal Ice Zone (MIZ) near Svalbard were used in this study. Diversity of sea types and forms in MIZ represents a complex task for automatic classification, but at the same time this allows a thorough evaluation of the performance of the algorithms under variable sea ice conditions. An extensive set of *in-situ* observations collected during the SIZEX'92 experiment is available for these images (Sandven et al., 1999).

The MIZ is characterized by transition from open water, through different types of new, young ice, broken first year ice to thicker, consolidated first year and multi-year ice. The advantage of the algorithms is that this transition between different sea ice classes is clearly seen in the classification results and is reflected on the BNN and LDA sea ice maps (Figure 13(c) and Figure 13(b)). From open water and pancake ice in the central part of the image strip the ice thickness increases towards North and in the upper images congealed multi-year and thick first year ice prevail. The diameter of ice floes (ice form) and as a result, surface roughness also changes. Because of the dynamical processes near the ice edge, wind stress and a collision of ice floes, smaller forms of first year ice dominate near the ice edge (red belt in Figure 13(c) and Figure 13 (b)). In the interior of the ice, congealed, smother first year ice exist.

Multi-year ice congealed with first year ice in the upper part of images appears as a noisy pattern. The borders of separate small floes are not fully delineated in the LDA classification map (Figure 13(b)). On the other hand, the BNN algorithm tends to attribute the congealed mixture of multi-year and first year ice to a bigger, more homogeneous region of multi-year ice. As a result this "zone" structure of MIZ is more evident in Figure 13(c). Some disadvantages of the algorithms are clearly seen in the central parts of the strips where the bright regions of pancake ice are classified as multi-year ice. Again, these misclassified regions are bigger and more homogeneous for the BNN algorithm. Therefore, on a qualitative scale, there is no evident superiority of either one of these algorithms for multi-year ice classification.

This was the first application of NAD algorithm for sea ice classification, and the areas of multi-year ice were not selected for training. As a result, multi-year ice in the upper left-hand corner of the image is left unclassified (Figure 13(d) and Figure 12).

The lower half of the images contain mostly open water and several types of new ice. Due to the high variability of the backscatter coefficients of open water depending on wind speed and forming of new ice, the depicted ice situation is complex for visual analysis as well as for automatic segmentation and classification. The very dark and bright regions in the central part of the images are correctly classified by all algorithms (Figure 13(b)-(d)) as grease ice (new ice) and open water, respectively. But in the lower part of the strips (not shown in Figure 13) where open water regions appear darker due to lower wind speed or the beginning of grease ice formation, these open water regions are misclassified as first year ice. The latter illustrates the necessity of the features describing spatial relationships between different image segments to be included in the sea ice classification algorithm.

Another important feature of the algorithms is classification of pancake ice which has a bright swirling pattern on the image. The biggest part of it is classified correctly by BNN algorithm, some part of pancake ice is misclassified as open water by LDA algorithm and almost all pancake ice is misclassified as open water by the NAD algorithm. The latter is because pancake ice was not defined during training procedure for the NAD algorithm.

The results of this comparison show the need of more careful selection of sea ice classes and the improvement of training procedure for the NAD algorithm. Information on the relative position of different image segments in the MIZ would be very useful for sea ice classification. In their current implementation, the BNN algorithm slightly outperforms the LDA algorithm for classification of pancake ice.

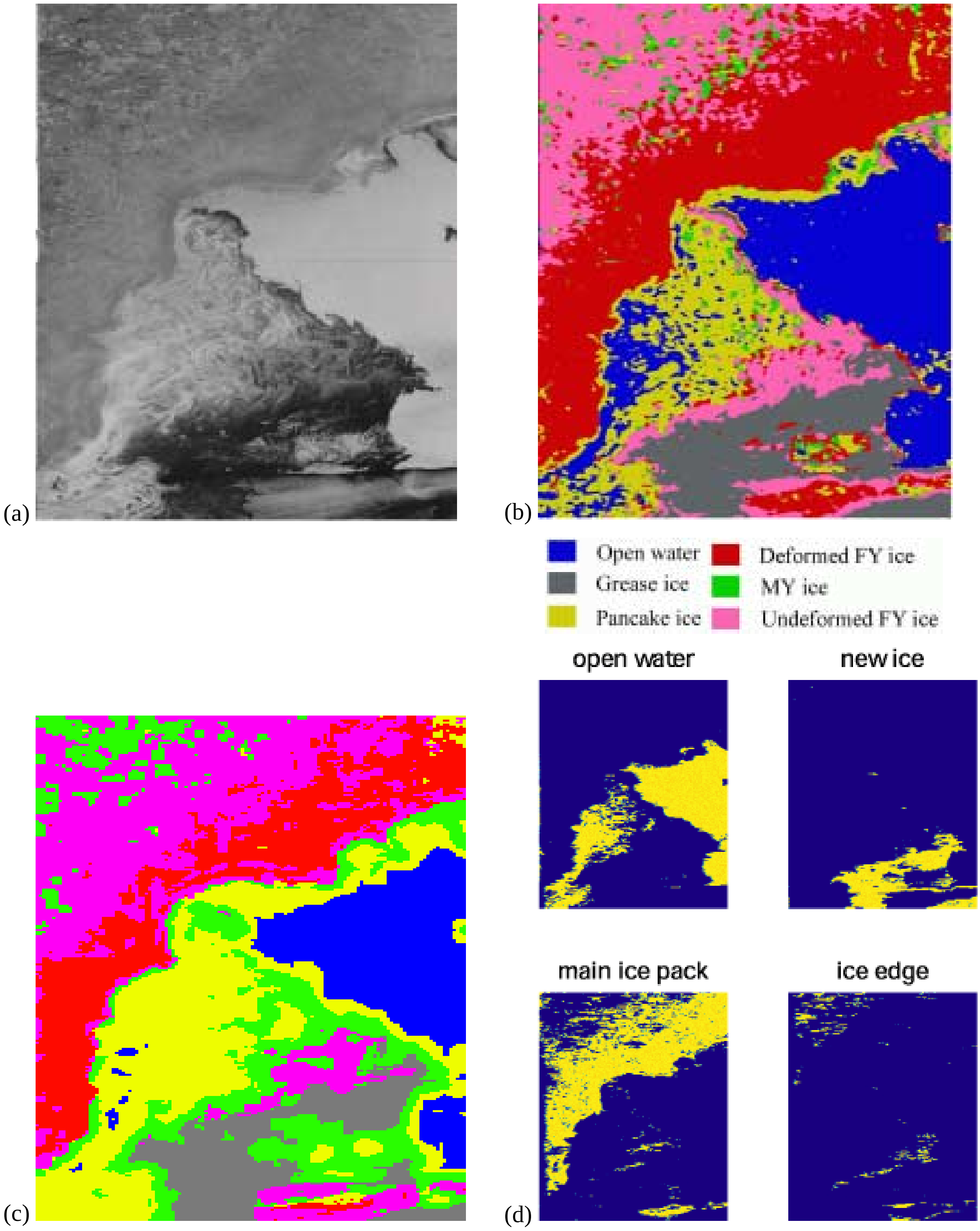


Figure 13 ERS-1 SAR image from 5 March 1992 (a), and classifications made by the LDA (b), the BNN (c) and the NAD (d) algorithms.

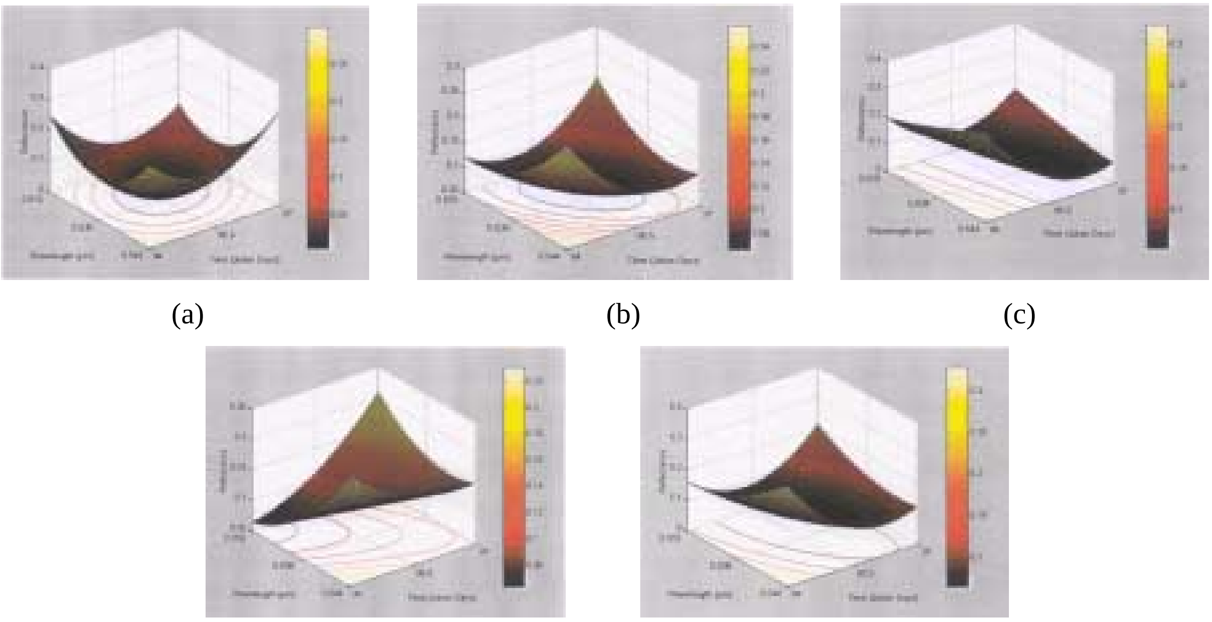
2.5.3 *STRS applied to forest phenology and sea ice monitoring*

Two examples of STRS-based cross-domain analysis were tested by UNOTT: a study of forest phenology and an attempt at sea-ice monitoring.

<u>Study of forest phenology</u>

Following the crop classification analysis (§2.3), the work was extended to test the STRS-based classification procedure on a different area of interest: forest phenology (Cohen *et al*. 2001, Coppin *et al*. 2001). Although the same basic methodology was used, the forested area was classified according to age classes using images acquired over a 5 year period (in contrast, the agricultural area was classified on the basis of different crop types over a single growing season). Again, classification was also performed using a single image for comparison with the STRS-based classification.

The forested study area was Kings Forest, located near Thetford, Cambridgeshire, UK. This area was dominated by compartments of various ages of a single tree species (pine). That is, each compartment contained pine trees of a single age, but the ages of the compartments ranged between approximately 5 and 65 years. Five SPOT HRV images acquired in June in consecutive years (1994, 1995, 1996, 1997, 1998) were used for analysis. Forestry Commission records were acquired to generate a ground truth data set. Five age classes were selected for analysis (<8 years, 8-18 years, 18-38 years, 38-58 years, >58 years) and per-pixel classification was performed using a single-date image and the STRS-based approach (Figure 14).



(a) (b) (c)

(d) (e)

Figure 14 Analytical polynomial trend surfaces and contours for pine pixels aged (a) <8 years, (b) 8-18 years, (c) 18-38 years, (d) 38-58 years and (e) >58 years.

Overall classification accuracies, kappa coefficients, variances and *Z* values are presented for the single-date and STRS-based forest classifications (Table 7). Of the two classification methods, the STRS-based approach was markedly more accurate. For instance, the overall classification accuracy of the STRS-based classification was 87.4%, considerably higher than that of the single-date forest classification (72.9%). There was a significant difference between the performances of the two forest classification methods ($Z = 2.83 > 1.96$).

Table 7 A comparison of accuracy measures for the two forest classification methods. *Z* values in **bold** typeface indicate significant improvements in the performance of the classifiers at a 95% confidence level (critical value = 1.96).

Accuracy measure		Forest classification method	
		Single-date classification	Multitemporal classification
Overall classification accuracy (%)		65.3	78.5
Kappa coefficient		0.610	0.731
Variance		0.000834	0.000999
Z values	*Single-date forest classification*	21.12	
	Multitemporal forest classification	**2.83**	23.13

Overall, it is clear that STRS-based classification is significantly more accurate than traditional single-date classification for determining forest age (and, as demonstrated in §2.3, crop) classes. The STRS approach has four particular strengths. First, multisource data can be used since the interpolation procedure accounts for irregularly spaced spectral and temporal measurements. Second, data points obscured by clouds can be filtered out throughout the interpolation and parameterisation procedures. Third, the use of function coefficients rather than pixel values at the classification stage reduces the processing requirements considerably. Fourth, a description of the spectral response of each pixel over the growing season is provided. This latter point has significant implications for wider adaptation of this technique, such as in crop yield prediction.

Study of sea ice monitoring

Exploratory analysis was performed to test the potential of adapting the STRS-based classification technique for sea-ice monitoring using SAR and reference data provided by NERSC. Various procedures were examined, including: (i) orbital co-registration of the images using ephemeredes data since there is no possibility of identifying static ground control points, (ii) hierarchical cluster analysis to identify meaningful clusters, (iii) derivation of various discriminating features (e.g., local texture, analytical coefficients, etc.) for classification and (iv) unsupervised classification using self-organising map neural networks and isodata algorithms.

As expected, the STRS algorithm was not directly applicable for sea-ice monitoring. This is primarily because sea-ice is dynamic in both time and ‘space’ (that is, sea-ice distributions move according to currents, tides etc., in addition to changing characteristics due to temperature fluctuations etc.) but the STRS algorithm characterises change over only time, not space. Accurate sea-ice monitoring requires algorithms which are able to incorporate both temporal and spatial change simultaneously. In addition, the relatively rapid speed of change in sea-ice distributions means that accurate monitoring requires repeat data acquisition fairly frequently (ideally every few hours). Few current satellite sensors are able to make such data provision, although new instruments such as ENVISAT may increase the frequency of data acquisition and use of several instruments (using flexible methods such as STRS classification) may enable meaningful analysis.

3. Extrapolation to a wider environmental field

Keeping the overall goal of FET-ENVIS in mind, i.e. to examine the possibility of designing a cross-domain environmental information system (EIS), we invited researchers from other fields of remote sensing to a workshop in Bergen. The idea was to build up a European network of scientists in remote sensing applications and to identify common problems that could be solved by an EIS in the future. As the selection of the appropriate sensors is already determined by the temporal and spatial characteristics of the observed objects (see introduction to Section 2) the main question was, whether methods of data storage, preprocessing, analysis and visualization could be shared in a modularized manner among the users of an EIS.

3.1 Workshop results

3.1.1 Terrestrial Applications Session

Five presentations were made at the terrestrial applications session of the FET-ENVIS workshop (Table 8). These covered various topics, although there was a clear focus on quantifying and locating land cover (and, in particular, crop) distributions using various sources of remotely sensed imagery. To complement the analysis performed by Dr. Paul Aplin (UNOTT) on crop classification, Dr. Katarzyna Dabrowska-Zilienska (Institute of Geodesy and Cartography, Poland) presented research on the use of multisource remotely sensed imagery for monitoring crop health. In this case, both optical and SAR data were used to aid agricultural practices throughout Poland. In combination, research from UNOTT and the Institute of Geodesy and Cartography have the potential to develop crop maintenance systems yielding significant economic savings for the agricultural sector. A further useful addition to such systems could stem from the research presented by Dr. Peter Atkinson (University of Southampton, UK). Dr. Atkinson outlined work on increasing the detail and, therefore, the accuracy of land cover classification using super-resolution mapping. This involved the use of Hopfield neural networks to map the distribution of land cover ‘within’ pixels. This technique holds significant potential for the generation of accurately detailed crop inventories.

Table 8 Presentations at the terrestrial applications section of the FET-ENVIS workshop.

	Speaker	**Affiliation**	**Subject**
1	Dr. Paul Aplin	UNOTT	Generating spectral-temporal response surfaces for multitemporal classification
2	Dr. Katarzyna Dabrowska-Zilienska	Institute of Geodesy and Cartography, Poland	Crop Growth Conditions Estimated Using Optical and Radar Satellite Data
3	Dr. Peter Atkinson	University of Southampton, UK	Super-resolution mapping and spatially autoregressive processes: some key techniques for FET-ENVIS
4	Mr. Øyvind Dalen	NERSC	Use of high-resolution satellite imagery in refugee monitoring
5	Mr. Mohamed Babiker	NERSC	Water resources assessment in arid land based on remote sensing data

A suitable framework for the development of crop maintenance systems could be provided by geographical information systems (GIS). GIS have the ability to store and integrate data from multiple sources, and can be designed to perform advanced spatial analysis. Research related to this general subject of GIS-based crop management systems was provided by Mr. Øyvind Dalen and Mr. Mohamed Babiker (both NERSC). While the work presented by Mr. Dalen was not directly related to crop production, it has implications for GIS-based management systems incorporating land cover classification analysis. Specifically, the use of high spatial resolution imagery for refugee camp monitoring was described. In particular, imagery was used to identify land cover features, which could then be integrated with other spatial data sets in a GIS to aid the management of refugee situations. Mr. Babiker demonstrated the use of GIS to integrate a complex set of spatial data (derived from remotely sensed imagery and other sources) to identify groundwater supplies in arid areas. This involved various aspects of surface feature classification, including the identification of vegetation and soil distributions.

3.1.2 Marine Applications Session

Five scientists gave presentations at the marine applications session of the FET-ENVIS workshop (Table 9). Two application domains were in focus: sea ice classification and detection of oil spills on the ocean's surface. Dedicated methods for sea ice classification were presented by Dr. Bogdanov (NIERSC), and oil spill detection algorithms relying primarily on aircraft data and satellite data were presented by Dr. Zielinski (Optimare) and Dr. Espedal, respectively. The concepts and possiblities of real time data acquisition by coastal radar were presented by Dr. Ziemer. A coastal radar can provide real time current data, which is useful in oil spill monitoring. Bathymetry data can also be estimated from a land based radar. Finally, the sensor fusion algorithm presented by Dr. Steinhage is a potential candidate for cross-domain applications in a future EIS. Examples of use in marine pollution and sea ice classifications were shown for this algorithm.

Table 9 Presentations at the marine applications section of the FET-ENVIS workshop.

	Speaker	**Affiliation**	**Subject**
1	Dr. Andrey Bogdanov	NIERSC	Sea ice classification using texture parameters and neural networks
2	Dr. Axel Steinhage	RUB	Nonlinear Dynamics for Sensor Fusion
3	Dr. Oliver Zielinski	Optimare GmbH, Germany	Airborne remote sensing of marine oil spills and hydrographic parameters
4	Dr. Friedwart Ziemer	GKSS Research Centre, Germany	Possibilities of ground based radar observations in coastal monitoring
5	Dr. Heidi Espedal	NERSC	Detection of oil spill and natural film in the marine environment by spaceborne SAR

A problem that applied to both application domains were e.g. the need for data processing in (near) real time. This included the ability to distribute results of analyses to end-users in a reliable and cost-efficient manner. Satellite-based sea ice monitoring for support of tactical ice navigation requires data to be acquired and analysed within a few hours, including electronic dissemination of results to the icebreaker or other ice-strengthened vessel. For oil spill detection and monitoring there are even stricter requirements for rapid acquisition and processing of data, since pollution often occurs close to the coast leaving little time for launching counter measures such as deploying oil lenses.

Another issue of concern are the problems related to the integration of data from different sensors, e.g. data from airborne and satellite sensors, or from airborne sensors and in situ instruments. Standardisation of data formats and data transfer protocols were discussed as part of a potential solution, but it was recognised that developing a complete monitoring information system for the marine environment will require a number of IT elements, such as GIS, image processing, data fusion, classification and machine learning techniques, expert systems, etc. In addition to computer algorithms and tools for analysis and presentation, human expertise must be built into the system, adding more value to the measured or predicted data.

3.2 Identification of requirements for data and analysis

From the workshop discussions and from the work in the case studies we have identified a number of constraints and requirements that must be met by a cross-domain environmental information system: As described in the introduction to the four case studies, the basic parameters of remote sensing applications are the temporal and spatial scales of variations of the observed objects and the temporal scale of the loop from detection to decision. These parameters determine which sensors and methods of analysis can be applied and build the starting point for the attempt to develop a modularized architecture for the analysis of remote sensing data.

When trying to specify cross-domain multi-sensor analysis modules, it is, therefore, necessary to first identify these temporal and spatial scales. Depending on the way the sensor data is acquired, the information exists in the form of (1) images or series of images (e.g. from a satellite), (2) of one- or higher dimensional time series of sensor values (e.g. from an airborne sensor that scans the sea surface) or (3) expert knowledge in symbolic or sub-symbolic form (e.g. knowledge about physical characteristics of the object to measure). An important step towards a cross-domain analysis system is the definition of a generic data format which incorporates all these different representations. Every analysis module must then provide its own interface to this generic data format. A first step in this direction has already been taken with the sensor fusion algorithm described in section 2.2, which could be applied to satellite images for sea ice classification as well as to the time series data from the airborne oil spill detection.

The same is true for the representation of the results of the data analysis: in some cases the end-user needs an image as a result (e.g. a geometric representation of a rescue camp); in the other extreme just symbolic “yes/no” information may be required (e.g. for the question whether a specific class of crop is growing on a certain field). Therefore, the output of the analysis modules must be transferable into various forms of representation.

Finally, easy access to the data, the analysis modules and the modules for the representation of the output must be possible for the end-users even from remote locations (during field work for instance). Therefore, an access of the system through the Internet should be implemented too.

3.3 Outline of new proposed projects

Two new proposals were discussed during the project workshop and the final meeting. Tentative titles and abstracts are as follows.

Generic spatial data integration system for environmental monitoring applications

The objective is to develop a prototype system for data integration, analysis, and presentation of data used in monitoring two different environmental applications: agricultural water resource management and marine pollution monitoring, to serve decision makers, the general public, etc. The longer-term perspective is to adapt the prototype to many different environmental applications which use the same data sources (i.e. satellite data, aircraft data, meteorological data, etc.) and the same software tools (GIS, image classification and data fusion algorithms, etc.). Key users of such a system will be: (1) agricultural organisations in the UK, Poland, and Greece; and (2) marine pollution authorities in Germany and Norway.

Marine pollution observing system by integrated use of satellite and aircraft data

The objective will be to develop a demonstrator version of a marine pollution observing system that integrates available data sources (remote sensing, in situ and model data) and advanced analysis and presentation tools for customised generation of products for end-users. The proposal should exploit ENVISAT data, involve aircraft observations in several coastal regions, conduct joint aircraft and satellite observation campaigns, involve coastal radar in Germany, use both microwave (SAR, SLAR) and optical (spectrometer) remotely sensed data if feasible, integrate satellite and aircraft observations using GIS, databases, data transmission in (near) real-time, include algorithm development & validation, image processing and classification, as well as service development. Partners will have expertise in both aircraft and satellite remote sensing of oil spills, and in (near) real time services. Operational entities with responsibility for pollution monitoring and clean-up measures will also be included, either as full partners or as members of a user reference group.

4. Conclusions and Recommendations for the Future

The overall objective of this project has been to investigate methods for efficient extraction and synthesis of environmental information using multi-source data analysis methods, which have the potential for reuse in a wide range of environmental problems. Four complementary case studies were chosen from the partners' field of expertise. The selected case studies covered both applications from the terrestrial and marine domain, to ensure a broad basis for testing cross-domain application of algorithms and enabling extrapolation of generalized results from the study as a whole.

The case studies investigated problems related to sea ice monitoring at high latitudes, detection of marine pollution, agricultural crop classification and use of very high-resolution satellite imagery for support of human relief operations. A review of state-of-the-art was conducted for all case studies, and the partners has implemented and assessed multi-source data analysis algorithms for the three first application domains. In humanitarian relief operations EO-data have only recently started to be used. Analysis methods are therefore mainly based on interpretation by operators and automated methods are not used. However, as this application becomes more mature, it can potentially adopt automated methods from the three other application domains.

During this project the partners have contributed to developing and evaluating a number of advanced sensor fusion and classification algorithms in the field of multi-source data analysis. Specifically, dedicated algorithms have been developed and assessed for sea ice classification, detection of marine pollution and agricultural crop classification. These algorithms were found to give an equal or higher level of accuracy compared to results from other commonly used methods described in literature. For instance, the STRS-based classification can generate more accurate crop inventories than traditional techniques. In addition the STRS (spatial-temporal response surfaces) algorithm has been successfully applied to a forest phenology study, and has the potential to be adapted for use in other application domains, such as marine pollution. We have also addressed the problem of more general multi purpose sensor fusion algorithms by means of a unified representation of information as attractors of dynamical systems. The nonlinear attractor dynamics algorithm has been successfully applied to other domains than for which it was originally developed, e.g. in sea ice classification.

Besides detailed investigations in specific application domains, and case study-specific cross-domain application of algorithms, emphasis has been on outlining a methodology for describing the inherent properties of the processes and phenomena included in an environmental problem as well as the type of problem a particular algorithm is capable of solving. We have identified three basic parameters that can be used to categorize the four selected case studies: (1) the time scale on which the observed objects change, (2) the spatial scale on which variations occur and (3) the required temporal scale of the whole investigation cycle from detection to decision. These parameters have strong implications on which algorithms are suitable for analysis and classification, and on which sensors can be used to provide input data with the required spatial and temporal scale. The four selected case studies are rather different with respect to these three parameters. Therefore, it seems possible to extrapolate the results from our assessment study to other environmental applications. The proposed categorization scheme can be seen as a first step towards a methodology for describing and selecting suitable algorithms for a given problem.

External experts have been consulted during the project, by organizing a workshop on advanced environmental algorithms, where the invited scientists both presented their own work and in addition assessed the algorithms developed by the FET-ENVIS partners. These experts supported the idea of developing cross-domain algorithms that can be reused in many environmental applications. Key IT elements of a future cross-domain environmental information system (EIS) were discussed, including the need for a GIS framework with capabilities for integrating and fusing multi-source and in some cases multi-temporal data, various case-specific and more general data analysis and presentation tools, efficient and flexible data structuring, storage and retrieval facilities, and opportunities for capturing expert knowledge about the application domain.

The overall conclusions from the project are as follows:

- Partners have developed and assessed a set of multi-source data analysis algorithm for selected case studies, and in addition successfully applied two of these algorithms in another domain than for which it was originally implemented. The investigated algorithms represent state-of-the-art in the respective application domains.
- Development of cross-domain algorithms for extraction of environmental parameters on a wider basis has been motivated by the identification of three basic parameters that describe the nature of an environmental problem. Such a categorization scheme can enable an EIS to make a best match between candidate algorithms and specific problems using these characteristics (spatial and temporal scale of change, frequency of change, and time needed for detecting/classifying specific phenomena).
- Strong IT competence is needed for the development of a cross-domain EIS. Key subsystems and technologies will be, among others, GIS, data fusion algorithms, image processing, networks, etc. Standardization of data and metadata formats, communication protocols, algorithm and subsystem interfaces, as well as of the system development process itself, must also be in place to conduct a successful implementation of a demonstrator or pre-operational EIS.

From the above, our overall recommendations for continuing the FET-ENVIS project are:

- Integration of multiple spatial datasets (remotely sensed imagery, ground-based measurements, ancillary data) for combined analysis of environmental problems have been proved valuable for the four case studies chosen from the terrestrial and marine domain. However, more application-specific and potential cross-domain algorithms should be investigated to further widen the basis for developing a toolbox of generic algorithms for environmental applications. To enable integration and comparison of candidate algorithms, the corresponding computer programs must be formulated in a modularized form with standardized interfaces. This allows the use of different data processing and analysis modules with the same datasets within a joint EIS framework.
- The development of an EIS should be carried out by a multi-disciplinary team, with a strong involvement of end-users from various application domains. GIS technology will play a key role for managing and integrating multi-source data, and enable advanced combined analysis and presentation, tailored to specific end-users. Other cutting-edge technologies, such as flexible, semantic representations of data and metadata through XML-based standards, should also be investigated and appropriate parts included in the realization of a cross-domain EIS.

The partners will actively seek to continue work in the field of multi-source data analysis methods and environmental information systems, and are currently in the process of forming a larger consortium for preparing two new proposals for the Fifth Framework Programme.

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App. A. Management Issues

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Deliverables

No.	Title	Availability
D1	Project presentation	Public
D2	Review Phase Report	Public
D3	Dissemination and Use Plan	Public
D4	Draft 3-year RTD proposal	Confidential
D5	Final Report	Public

Public deliverables are available from the project's web site.

Presentations at workshops and conferences

- Axel Steinhage and Carsten Winkel: *A Robust Self-Calibrating Data Fusion Architecture*. In: Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, IGARSS 2000, IEEE-publications, Vol. III, pp 963-965 (Oral presentation in Hawaii, USA, July 2000).
- Axel Steinhage and Carsten Winkel: *Dynamical Systems for Sensor Fusion and Classification*. In Proceedings of IGARSS'2001, Sydney, Australia, 9-13 July, 2001 (Oral Presentation in Sydney, Australia, in July 2001).
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