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An algorithm review for CryoRisk

Nils Kristian Orthe
Øystein Godøy
Kjetil Melvold
Steinar Eastwood
Rune Engeset
Thomas Skaugen

5
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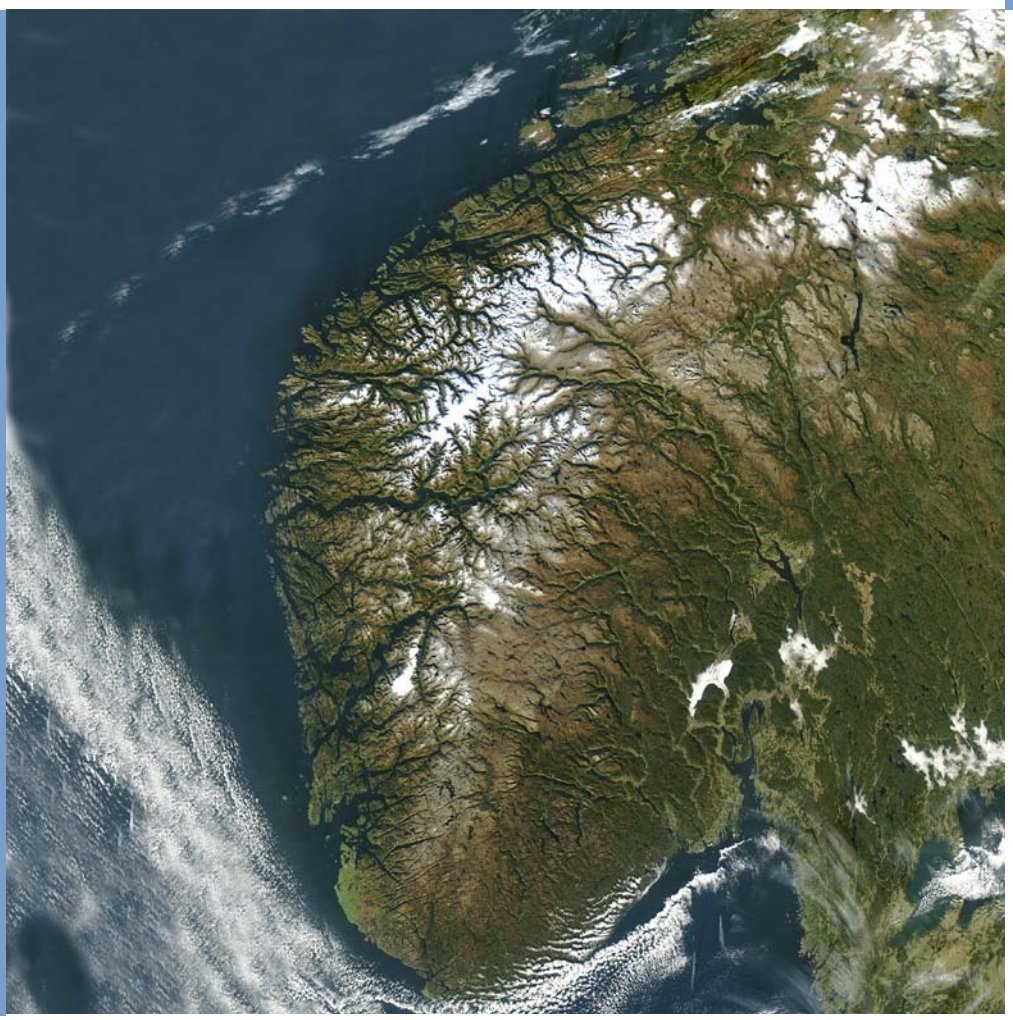

OPPDRAGSRAPPORT A

An algorithm review for CryoRisk

Norwegian Water Resources and Energy Directorate

2007

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An algorithm review for CryoRisk

Commisioner: Norwegian Space Centre

Editor
Authors: Nils Kristian Orthe (NVE), Øystein Godøy (METNO), Kjetil Melvold(NVE), Steinar Eastwood (METNO), Rune Engeset (NVE), Thomas Skaugen (NVE)

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Norwegian Water Resources and Energy Directorate
Middelthunsgate 29
Postboks 5091 Majorstua
0301 OSLO

Telephone: 22 95 95 95
Telefax: 22 95 90 00
Internet: www.nve.no

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Preface

This report is a deliverable in the project CryoRisk. CryoRisk is supported by the Norwegian Space Centre.

The main objective of CryoRisk is to modernise and expand the public services at NVE and met.no for monitoring the cryosphere using earth observation data.

Project participants are Nils Kristian Orthe (NVE), Kjetil Melvold (NVE), Zelalem Mengistu (NVE), Liss M. Andressen (NVE), Thomas Skaugen (NVE), Rune Engeset (NVE), Heidi Rutland Bache (NVE), Øystein Godøy (met.no), Steinar Eastwood (met.no), Hanne Heiberg (met.no) and Mari Anne Killie (met.no).

This report was written jointly by NVE and met.no.

Oslo, March 2007

Morten Johnsrud	Nils Kristian Orthe
Director of the Hydrology Department	Project leader

Abstract

The intention of CryoRisk is to establish a national production line for extraction of snow cover information from satellite remote sensing data. This production line will be shared between the Norwegian Water Resources and Energy Directorate (NVE) and the Norwegian Meteorological Institute (METNO), will be integrated within the existing operational systems and will serve the general public through well established interfaces at these institutions. CryoRisk focus on extraction of snow covered area from optical (AVHRR, MODIS, VIIRS, ...) and active microwave sensors (SAR). The focus is on sensors that are currently operational, or will be operational in the near future. For the optical sensors, discrimination of snow covered and not snow covered pixels will be performed as well as extraction of sub pixel information.

This report describes the algorithms considered for implementation within the operational system of CryoRisk. It builds upon the knowledge gained at NVE and METNO through several previous projects as well as the knowledge of optical algorithms at Norwegian Computing Center (NR) and of SAR algorithms at NORUT IT. The two latter have provided review reports (Solberg et al., 2007, Malnes, 2007) which have been used during the algorithm selection work.

The algorithm selection is based upon knowledge of existing operational systems, experimental systems and a cost-benefit analysis focusing on the intention of the project, to establish an operational service within the framework of the project. For pixelwise classification of AVHRR and MODIS, the NWCSAF PPS algorithm is defined as fallback, whilst the intention is to use a Bayes approach similar to the one used within the EUMETSAT Ocean and Sea Ice SAF for sea ice detection. The NWCSAF PPS algorithm can also be used for MODIS processing. Both results for AVHRR and MODIS will be compared with NASA MODIS products, in situ observations, as well as manually analysed AVHRR imagery. For sub pixel classification the Norwegian linear reflectance-to-snow-cover (NLR) algorithm will be used. For SAR the Nagler algorithm will be used. When using SAR for classification of open water, several algorithms will be tested. The most likely product is an unsupervised classification with manual post processing.

1 Introduction

The main objective of CryoRisk is to modernise and expand the public services at Norwegian Water Resources and Energy Directorate (NVE) and the Norwegian Meteorological Institute (**METNO**) for monitoring the cryosphere using earth observation data. To achieve this objective NVE and METNO will establish an operational national production environment for snow cover extraction from satellite remote sensing data. The project is funded by the Norwegian Space Centre (NRS)

This report provides an overview of existing snow cover area (SCA) algorithms and algorithms for open water classification (OWS) on water and rivers, and reflects the discussions leading up to the selection of which algorithms to implement. Norwegian Computing Center (NR) and Norut IT have also contributed to this report by delivering review reports on respectively optical snow cover algorithms and SAR based snow cover algorithms. A separate report describing the technical operational environment of the production line involving both NVE and **METNO** will be produced in 2007.

NVE has participated in earlier projects, EnviSnow, SnowMan and DemoSnø, where the aim was to develop snow products inferred from Earth Observation (EO) data and evaluate the usefulness in hydrological applications. This report builds on the results from these projects.

NVE has downloaded NOAA AVHRR data manually since 1995. These scenes have been manually geocoded and classified using NLR snow algorithm (Andersen, 1982). This method retrieves the fractional snow cover for each pixel. Cloud discrimination was also done manually with a threshold value adopted from each scene. A daily mosaic was generated from multiple scenes when possible. This scheme was heavily dependent on manual interpretation of each scene both for geocoding and classification.

METNO has worked with automatic cloud discrimination and snow and sea ice extraction from AVHRR data for many years (Godøy and Sunde, 1996, Godøy and Sunde, 1997, Godøy and Eastwood, 2002). This work was done through internal projects as well as external projects funded by EU and EUMETSAT (e.g. EuroClim, OSISAF).

The selections of algorithms in this report will form the foundation of the production line being developed. Automatic procedures in all parts of the processing chain are desirable, but NVE will permit some manual work if this results in better products from a hydrological perspective. Work done by Udnæs et al. (2007) using satellite derived SCA to improve runoff modelling concludes that a manual inspection of the SCA scene is recommended to avoid erroneous updates.

It is important to be flexible and recognize that the requirements can change and that the operational environment must be able to adopt (e.g. by adding new sensors or new algorithms). However, the framework as defined through the operational environment will not change rapidly and is an important point in the cost-benefit analysis prior to operational implementation.

Open Water Surface (OWS) maps are very useful for discriminating ice-free and ice-covered lakes and rivers during freeze-up and break-up situations. OWS maps can be

used in an overlay analysis with maps of lakes to create maps of ice covered lakes. Lake ice has a strong influence on local energy and water exchange, lake-ice freeze-up and break-up dates are also good indicators of regional climatic variability. It is also very useful for to assessing safety of traffic and transport on lakes and will be used to improve our ice information system “ismelding” by increasing spatial cover in regions with sparse data.

In Norway, the development of ice-cover on rivers is a major concern for water resource management, hydropower generation and flood damage prevention. Rivers normally freeze up in an upstream direction in a highly complex and dynamic process. Of particular concern is the formation of consolidated ice cover from thinner layers of frazil ice, which in turn can cause ice-damming and flooding over large areas. The severity and economic impact of floods related to ice dams is exacerbated by the danger of post-flooding freeze-up. In order to assess the likelihood of impending floods, it is imperative to monitor the development of ice-cover throughout the freeze-up.

Key parameters required to assess the danger of flooding due to ice jams include location, extent and structure of the ice field. However, a systematic determination of these parameters is difficult to achieve using conventional, field-based and aerial surveillance methods. In remote and inaccessible areas, frequent surveillance can be prohibitively costly. Under these conditions, EO has emerged as a promising tool to collect information on river ice development over large areas repeatedly and consistently throughout the ice season.

2 User requirements

2.1 NVE

2.1.1 Application

NVE will use snow cover area retrieved from EO data for:

1. The direct assimilation of snow covers into hydrological models.
2. The manual interpretation of satellite images (done by flood forecasting group).
3. The validation of snow models which are based on interpolated precipitation and temperature.

2.1.2 Sensors

NVE's primary interest in using EO data is mapping snow and snow/ice over lakes and rivers. All sensors capable of doing this are of interest.

NVE intends to use NOAA AVHRR, MODIS from Terra/Aqua and RADARSAT 1. ENVISAT MERIS and ASAR will also be considered since the sensor is being made operational by ESA with the planned Sentinel satellites. MERIS is an interesting sensor with its high spatial resolution, but the ability to discriminate snow/cloud is a problem, because in the visible near infrared (VNIR) snow and most clouds have very similar spectral characteristics (Malcher and Rott, 2004).

2.1.3 Spatial and temporal coverage

Spatial coverage

NVE is interested in observing national coverage of snow from satellites. At present hydrological models at NVE do not use input from a wider area in contrast with numerical weather models. This requirement could be changed in the future as new hydrological models are developed and used. Sensors which give a good coverage of Norway are NOAA AVHRR, Modis ENVISAT MERIS/ASAR and Radarsat 1/2. The spatial resolution of the instrument becomes more important when the catchment size is small and the variation in topography is large. Because of this the MODIS instruments on Terra and Aqua is the preferred optical sensor with its spatial resolution at 250 - 1000 metres. ENVISAT MERIS also has good resolution with its 260x290 metres pixel size. Figure 1 shows some examples of catchments areas.

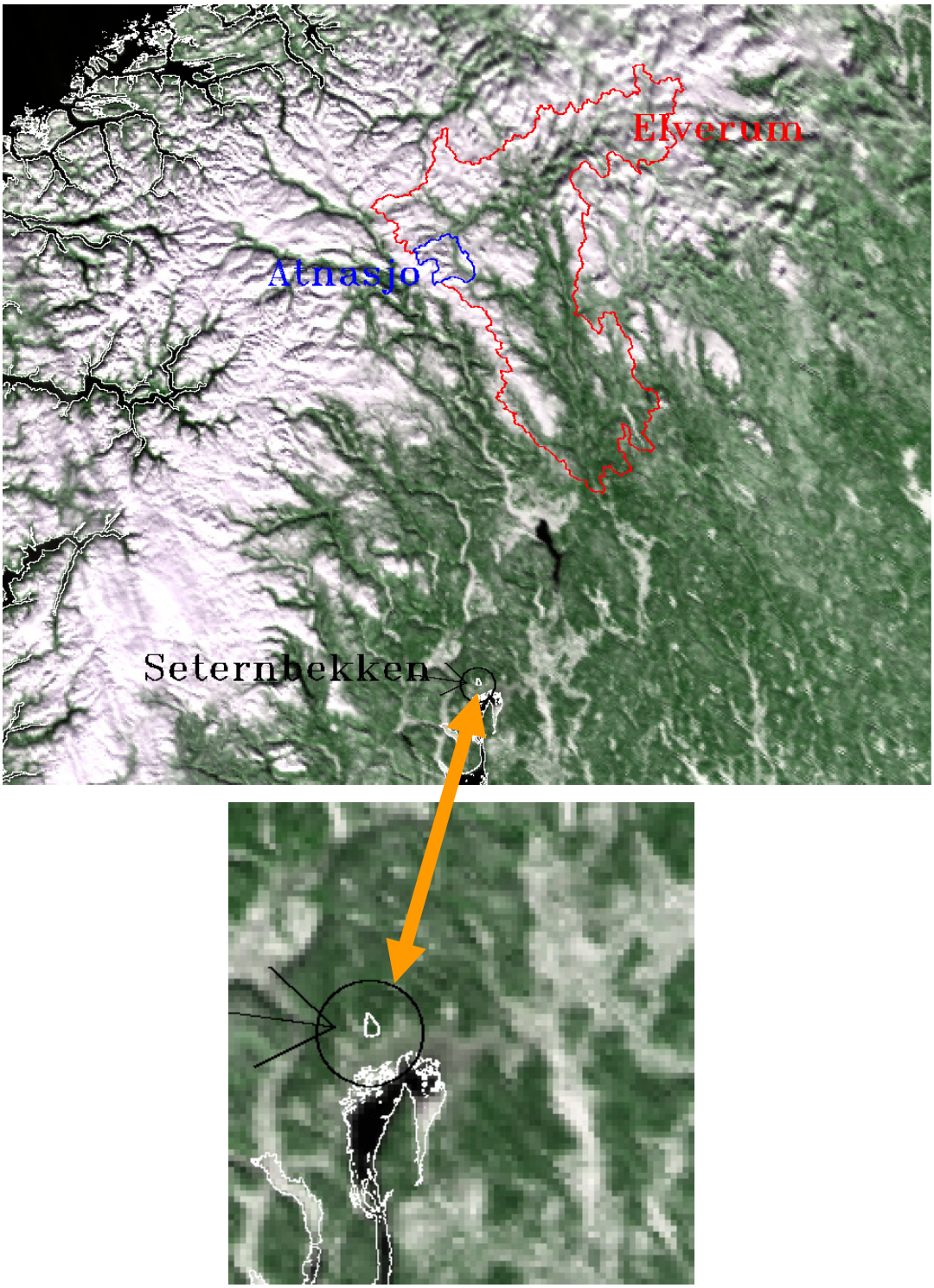


Figure 1 Top panel shows catchment areas of various sizes (large, medium and small). Bottom panel shows Seternbekken catchment which is near Oslo. This is one of the smallest catchments for which NVE has implemented a hydrological model (6km^2).

With open water classification the spatial resolution must be sufficiently high such that the presence and absence of ice within the lakes and rivers can be resolved. The Radarsat 1 ScanSAR scenes, which are provided by KSAT have a spatial pixel resolution of 25x25

metres. This is a very good resolution and should be adequate for open water classification on lakes and rivers. Initially, we will look only at lakes with an area larger than 5 km^2. The geographical area to be covered is mainland Norway. However, initially we will concentrate on central southern Norway.

Temporal coverage

Snow coverage varies in time due to changing temperature, radiation and other meteorological variables. NVE's main focus is in the melting period, typically from March to early July, because of its impact on floods. As SCA may change rapidly (within days) during the melting period, we propose a minimum temporal SCA resolution of 7 days during the melting period. This requirement may change as we gain more operational experience.

The bulk water temperature (the average temperature between the lake surface and lake bottom) at which lakes freeze over is related to fetch, with small lakes freezing at a bulk temperature of 2-3°C and large lakes freezing at a bulk temperature of 1°C (Scott, 1964). Lake depth and volume are also important parameters of freeze-up (Stewart and Haugen, 1990). The combined effects of lake fetch, depth and volume result in different freeze-up times from lake to lake. **In order to map change in OWS and thereby freeze-up times, a relatively large temporal coverage is needed because lakes of different size, fetch and depth freeze up at different times.** The temporal resolution must be high enough to identify quickly changing patterns in freeze-up and ice breakup in the area of interest, with daily to weekly time series of images as a practical goal.

The minimum time resolution accepted for open water surface is a weekly product that is updated on a daily basis using all available satellite data to reduce the effect of clouds. Only the most promising satellite data (e.g. for optical sensors only images with reliable discrimination between clouds and snow/sea ice will be used) will be analysed, thus some human inspection is accepted in the process of OWS classification. This product should be available from mid-December to May.

2.1.4 Geolocation accuracy

Geolocation accuracy is important to NVE. NVE has hydrological models in catchments ranging in size from 5 km^2 to 15450 km^2. Satellite derived SCA based on GIS data could give large errors because of transfers in x and y image directions when compared with catchment boundaries in a given projection. Figure 2 shows how Atnasjø catchment area is distributed with respect to height above sea level. From this figure we can see that changes in the x and y direction can give erroneous results if the catchment boundary crosses the snow line (i.e. parts where the catchment boundary lies near a valley).

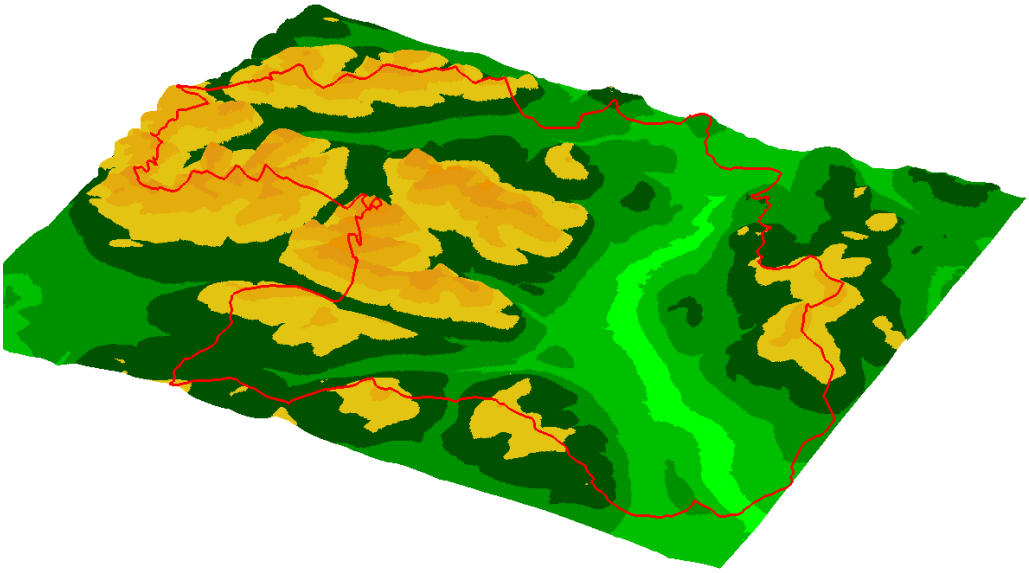


Figure 2 Overview over Atnasjø catchment area. The area ranges from 701 - 2153 m.a.s.l.

Geolocation accuracy has been manually checked from geocoded Radarsat ScanSAR scenes delivered from KSAT. The geolocation accuracy observed in the scenes varies between 3 – 9 pixels, where each pixel is 25x25 metres. This is considered good enough when observing SCA, but could be a problem for open water classification. Figure 3 gives an example where GIS data is infused into a geocoded scene produced by KSAT.

Geolocation becomes even more important when algorithms are used to classify open water. It is then important to classify only the pixel which lies within the boundaries of the specified lake or river.

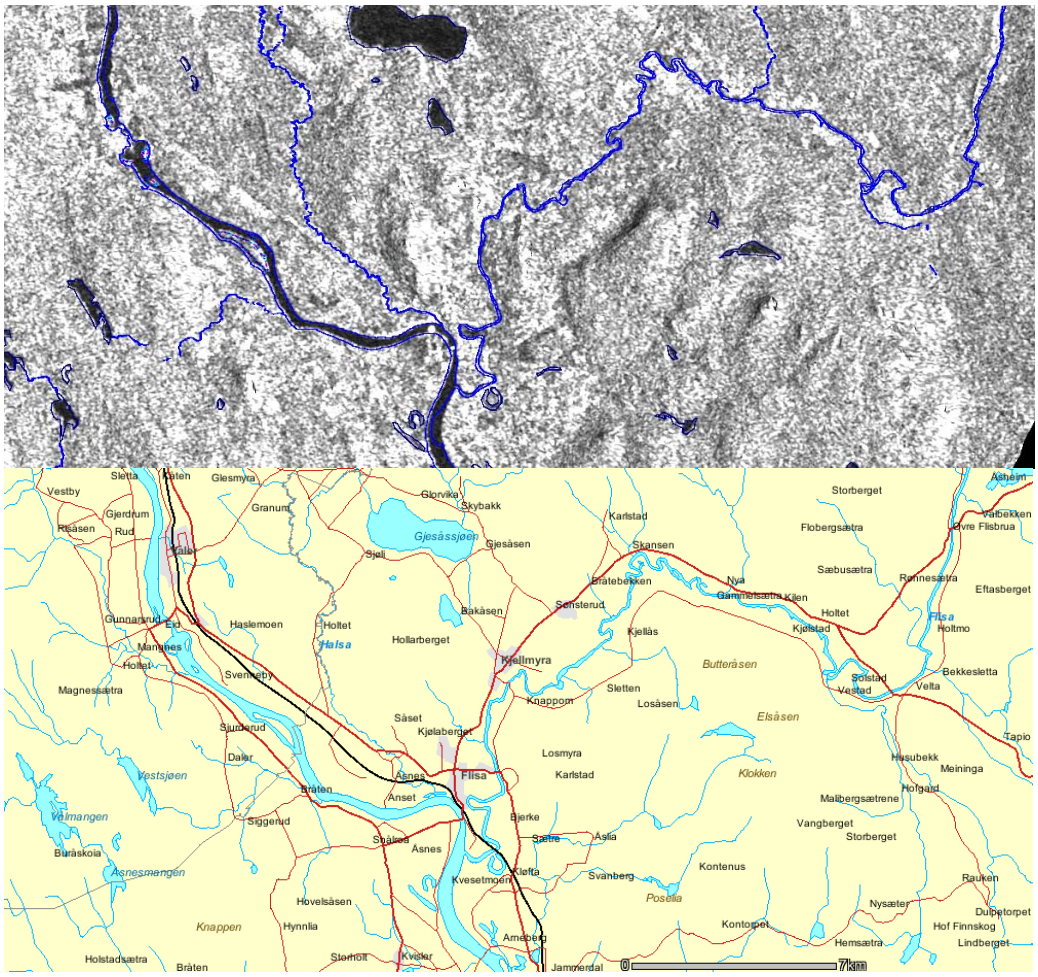


Figure 3 Radarsat 1 ScanSAR narrow scene showing infused GIS data over rivers and lakes. The large river is Glomma which runs through Flisa.

2.1.5 Snow and cloud classification

The relationship between snow cover area (SCA) and snow water equivalent (SWE)

The hydrological models used at NVE attempt to assimilate snow cover from EO data. This work tries to implement algorithms that use observed SCA to update the snow reservoir (mean areal snow water equivalent, SWE). The analytical link between SCA and SWE is found when the hydrological model at all times formulates an analytical expression of the statistical spatial distribution of SWE. This work has revealed the very non-linear relationship between SCA and SWE, i.e. an error of 5 % in the classification of SCA may have a large effect on the estimate of SWE. This is denominated in Table 1. For rather modest values of SWE, the update of SWE appears to be fairly linear, but for large values of SWE, we see that modest differences in SCA result in a huge difference in the updated SWE. The reason for this is that the spatial distribution of SWE for large values of SWE tends towards a normal distribution, and small changes in SCA with SWE normally distributed involves quite a dramatic change in SWE. This is not the case for small values of SWE where the spatial distribution of SWE is more skewed.

Table 1 The relationship between SCA and SWE from Akslen catchment, Jotunheimen.

Modelled SCA	Observed SCA	Difference SCA (%)	Modelled SWE	Updated SWE	Difference SWE (%)
1.0	0.91	109	178	147	121
0.77	1.0	77	111	132	84
0.53	0.94	56	65	100	65
1.0	0.9	111	454	281	162
1.0	0.89	112	762	365	208

Sub-pixel information versus snow/ no snow

The implication of precise snow cover given in Table 1 shows the importance of having sub-pixel information. Sub-pixel information is also important given the size of the catchments.

For optical sensors, the reliable discrimination between clouds and snow is of vital importance. The radiometric signature of clouds and snow is quite similar and classification has proven to be difficult. This is especially the case when considering sub-pixel information, where opaque clouds can contaminate the spectral signature of the underlying snow and give false fractional snow values. Because of this NVE should favour a conservative cloud detection algorithm.

Open water classification

The principal aim is to establish an operational processing chain in order to monitor OWS for lakes larger then about 5 km^2 and hopefully some of the largest rivers (i.e. more than 100 m wide), during winter time, applying three key operational satellite sensors: NOAA AVHRR, Terra MODIS and Radarsat (1/2) ScanSAR. Multi-temporal information will be used, such that radar data fills time gaps in optical acquisition. For validation we wish to use higher resolution satellites (Landsat ETM+, Terra ASTER/MODIS, Radarsat-1 S7) if data is available in addition to ground observations. OWS presently needs pixel to sub-pixel information, due to the relatively small features that should be mapped.

2.1.6 Data access and operational environment

Data access

It is preferable to access data through a defined machine interface, such as automatic FTP downloading, Web Coverage Service (Open Geospatial Consortium) or some other open standard interface.

NVE has previously manually downloaded NOAA AVHRR images for operational use. NVE wish this function to now be automated. Today NVE accesses NOAA AVHRR with ftp from METNO (done by CryoRisk project 2006). This gives us access to all NOAA AVHRR data in near real time. A similar approach is being set up between NVE and KSAT which delivers geocoded Radatsat 1 data to the project. Access to MODIS data is done through an automated FTP interface to NASA. The MODIS data available from NASA lags by approximately one day. This is acceptable in an evaluation phase, but

NVE hopes that collection of MODIS data can be done through automated schemes at METNO, either directly from KSAT or through EUMETCAST from EUMETSAT.

Operational environment

NVE will divide the operational environment into

1. Pre-processing(re-projection): This will be done using in-house software using idl as the programming language and ENVI as a library.
2. Algorithm implementations: Same as pre-processing.
3. Distribution: this will be done using Microsoft .Net platform which is NVE's preferred development environment.

2.2 METNO

2.2.1 Application

METNO will use the remote sensing products developed and produced through CryoRisk for several purposes:

1. It will be evaluated for input to HIRLAM NWP (possibly also UM NWP) either within the snow analysis of HIRLAM, or as a full snow analysis including in situ observations outside HIRLAM.
2. It will be evaluated for input to the UV-forecast which uses forecast fields from NWP models and a Radiative Transfer Model (RTM), either as a stand-alone product or through an analysis involving in situ observations as well.
3. It will be evaluated for use in climatological products involving interpolated observed precipitation and temperature.
4. It will be used a stand-alone product for subjective interpretation by operational forecasters and the public.

2.2.2 Operational environment

The operational environment at METNO is a 24/7 year round production environment. Job control is performed using ECMWF Supervisor Monitor Scheduler (SMS), with manual intervention when absolutely required. Usually applications are designed to minimise human intervention and if this is required, the application should explain in detail how to handle the exception. The operational suite runs on Linux computers extensively utilising Open Source software to minimise operation costs. The programming languages used are C, C++ and Fortran, and the job script language used is Perl.

Distribution will be done through the normal interfaces operated by the institute. At present this is through FTP/HTTP and using ordinary web pages, but Web Services and OGC technologies are being developed, although not as part of CryoRisk.

2.2.3 Sensors

METNO is focused on sensors being operational or expected to become operational within reasonable time. For optical sensors, the focus has been on AVHRR as this is operational and is expected to continue operation beyond reasonable time scales. It is useful for many applications, covering both atmospheric and surface characteristics, an

essential feature for METNO. Furthermore, METNO has a direct readout station for AVHRR in Oslo and also receives data from the North Atlantic through EUMETSAT EUMETCAST. VIIRS is expected to become the operational successor to AVHRR, MODIS is regarded as a prototype of this and thus an interesting sensor. METNO is currently examining various sources for a real time access to MODIS data (e.g. through EUMETSAT EUMETCAST), until this is in place FTP access through NASA will be used. Data access to the sensors listed above is rather straightforward. MERIS is a programmable sensor which measures in 15 bands in the region 0.41-0.9µm. These bands may be shifted in position and bandwidth. The lack of information from the 1.6µm or 3.7µm regions complicates discrimination between snow and clouds (see e.g. Malcher and Rott, 2004). The fact that it is programmable and may change behavior complicates the potential operational use of the sensor. The use of active microwave sensors such as SAR has not proven reliable year-round and is thus not of major focus to METNO.

2.2.4 Geographical coverage

The geographical area to be covered is determined by the requirements of the applications (NWP and RTM models) using the output of the project. This implies that the northern Atlantic and surrounding land areas should be covered (Figure 4). METNO has at present no need for sub-pixel information, focus is instead put into regular updates and regional coverage. The minimum time resolution accepted is a daily product which uses all available satellite data within one week to reduce the effect of cloudiness. This product should be available year-round. Failing to identify snow cover produces an error of magnitude 2-5 Kelvin (or more) in the surface temperature at 2 metres (Homleid and Ødegaard, 2000).

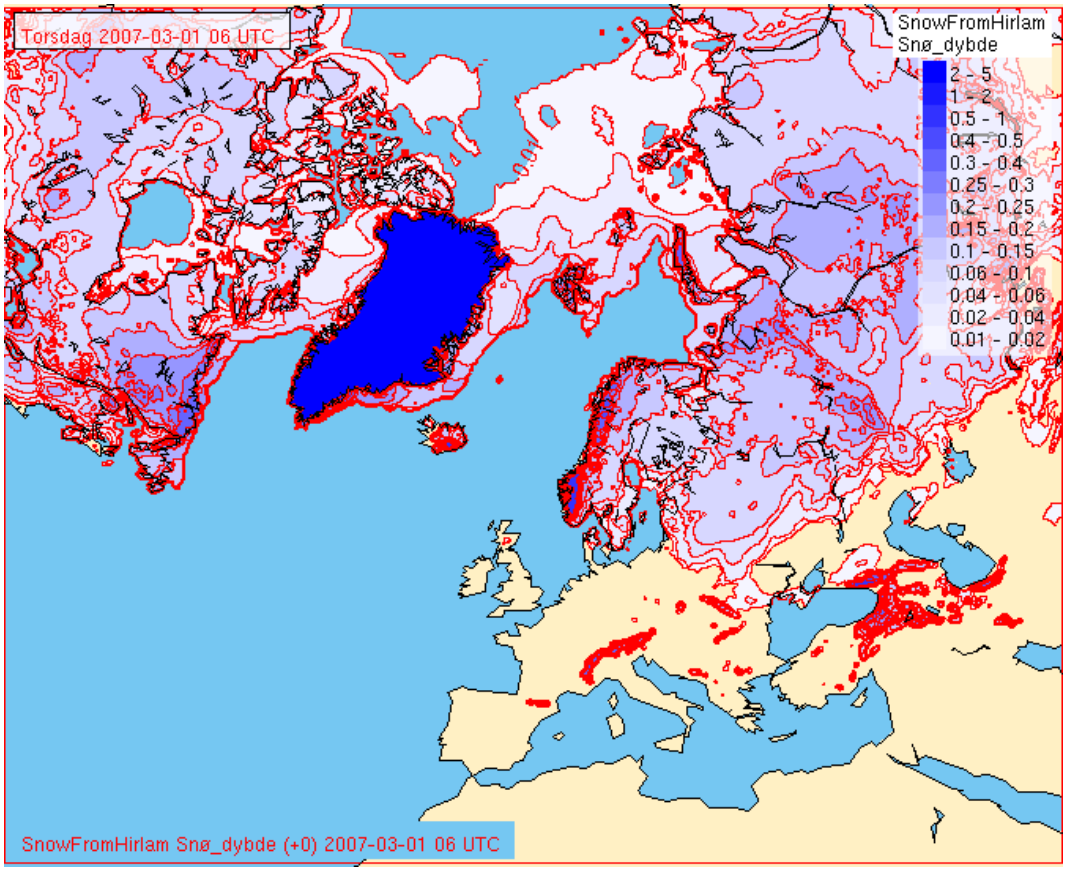


Figure 4 The present minimum area to be covered for use with HIRLAM.

2.2.5 Performance

Regarding optical sensors (which are the main focus of METNO), reliable discrimination between clouds and snow/sea ice is of vital importance. This has proven difficult using automated schemes as the radiometric signature of clouds and sea ice/snow is rather similar. At METNO a reliable automated scheme handling both cloud/no cloud and snow/no snow identification is a requirement. The methodology implemented should know its limitations (e.g. season, solar conditions, etc.) and skip scenes/areas where it is expected to fail. The scheme implemented should be fully automated and where dynamic thresholds or region specific settings are required this should be done automatically. The use of surface or atmospheric information from a NWP model is accepted.

The remote sensing products will be integrated with other supporting data (e.g. in situ observations) through an analysis scheme. This scheme will be specified in detail for the specific application (i.e. different procedures for input data to NWP, RTM models and climatological purposes).

3 Auxiliary data available

An overview over available data from NVE and METNO is given. Some of these data can be used in the classification algorithms and some would be valuable in the validation of snow products. The data is divided into dynamic data, which is data METNO and NVE measure, or models either in real time or historical. The other source is static data; typical data here would be standard GIS data.

3.1 In situ observations

3.1.1 NVE

NVE has a number of gauging stations available in real time. Most of these stations measure water discharge, but the air temperature is also measured for most of them. NVE has currently 22 snow pillows, which measure snow water equivalent. NVE also collects a number of snow course measures taken by local power plants. Those data are not collected in real time, but could be used in validation.

OWS is not reported directly in the NVE database. However ice cover and ice thickness observations are available only from a limited number of lakes. These stations report on a different time basis; often only once or twice a year.

3.1.2 METNO

Snow cover observations are available from the global network of synoptical stations observing the snow cover and depth once a day and reporting in real time over GTS, the meteorological network. There are about 100 synoptical stations observing snow cover in Norway. In addition there is a national network of precipitation stations observing daily precipitation, snow cover and snow depth. These stations report on different basis, in near real time using mobil telephone SMS or through mailing the observations once a week.

Some of the in situ data are available through Web Services interface.

3.2 Numerical weather prediction (NWP)

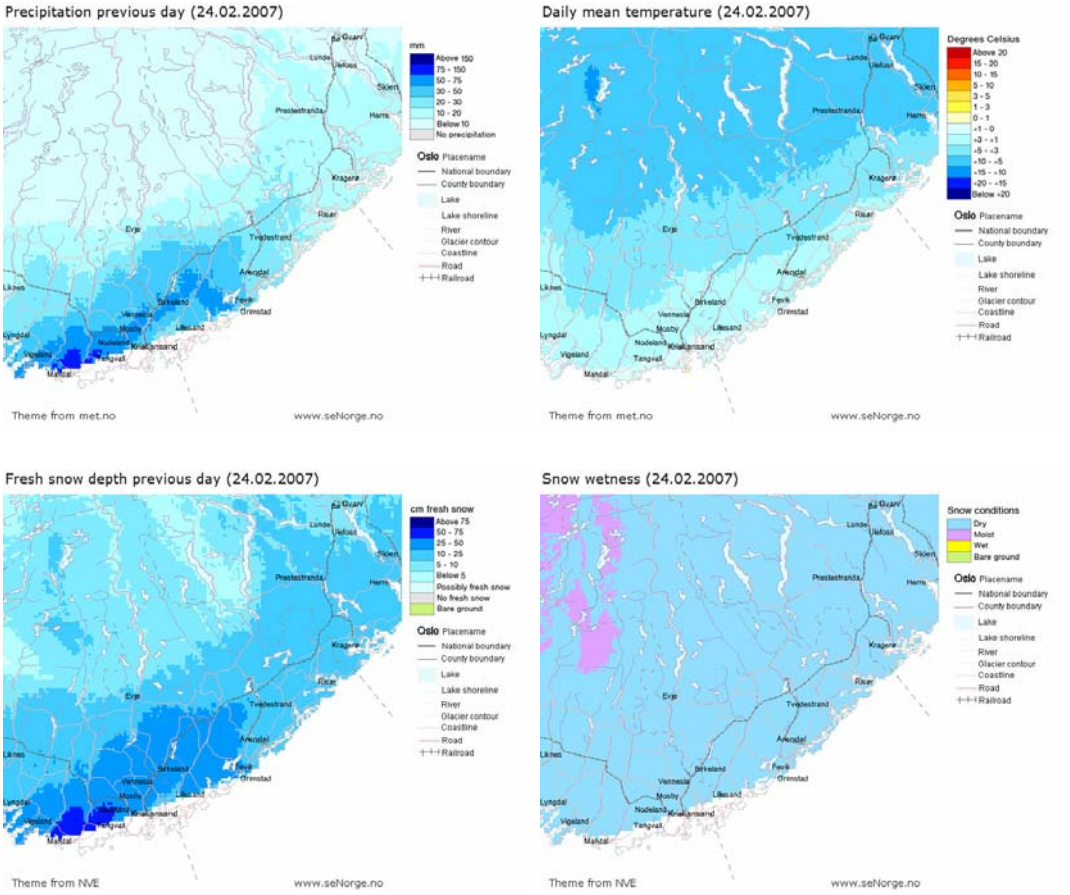
METNO operates a range of NWP models. The most commonlt used is HIRLAM, which is operated at various spatial resolutions and geographical coverage. The spatial resolution varies from approximately 4 to 20 km and depends on the geographical coverage needed. This information should be used carefully as the snow cover produced from satellite data will probably be used in the NWP model again in the analysis.

3.3 Gridded precipitation and temperature observations

All available observations from the public meteorological network observing air temperature and precipitation are used to interpolate fields of daily values at 1 km by 1 km resolution for Norway (Tveito et al. 2000, Engeset et al. 2004). Gridded data are available from 1961 and updated every morning at about 10 a.m. Temperature is observed at about 150 stations and precipitation at about 630 stations at present.

3.4 Gridded snow maps

National coverage snow maps are produced on a daily basis using a gridded snow model operating on the 1 km^2 / one-day grids of precipitation and temperature described above (Engeset et al. 2004a,b). All relevant snow simulations are presented on the web site www.seNorge.no together with the meteorological data (further description of web site, the web services and the data is available at www.seNorge.no). Figure 5 shows examples of gridded weather and snow data for the 24 h period ahead of 7 a.m. on 24 February 2007, when extreme snow fall disrupted traffic and damaged infrastructure in South Norway.



Extreme snow fall destroyed the roof of the post terminal in Kristiansand.

Photo: Tor Erik Schrøder / SCANPIX

The city bus service in Kristiansand was suspended. Photo: Tor Erik Schrøder / SCANPIX

Figure 5 Maps of precipitation, temperature, snow fall and snow wetness, and examples of snow-related problems on 24 February 2007. Graphics from www.seNorge.no and www.aftenposten.no.

3.5 Soil type

3.5.1 NVE

NVE has access to a land cover characterisation from The Norwegian Forest and Landscape Institute (through Norway digital). This theme layer has a pixel resolution of 25x25 metres. Soil type covered areas are: crop land types, bog, forests, mountains etc.

3.5.2 METNO

USGS Global Land Cover Characterization (GLCC, see http://eros.usgs.gov/products/landcover/lulc.html) is currently being used for several projects at METNO. The spatial resolution of this is about 1.0 km resolution and it contains 24 classes of land cover types based upon AVHRR data and other data sources. The reliability of this dataset has been questioned within the meteorological community.

3.6 Digital elevation model (DEM)

3.6.1 NVE

NVE has access to a DEM with a pixel resolution of 25 metres. NVE is given access to this dataset via a collaboration called ND (Norway digital) from Norwegian mapping authorities.

3.6.2 METNO

USGS GTOPO (http://edc.usgs.gov/products/elevation/gtopo30/gtopo30.html) is a global digital elevation model which has been used in several projects at METNO. Although it has some deficiencies over Norway, it provides the area coverage required by METNO applications.

4 Algorithms

4.1 Review of optical and SAR-based algorithms for snow and cloud cover monitoring

In order to use knowledge aquired during several research projects on satellite-based snow monitoring, Norwegian Space Centre and NVE/METNO asked the Norwegian Computing Centre (NR) and Norut IT (Norut) to provide their reviews of algorithms (Terms of Reference are shown in Table 2. NR reviewed algorithms for snow and cloud cover monitoring using optical sensor data (Solberg et al. 2006) and Norut IT reviewed algorithms for snow cover monitoring using SAR data (Malnes, 2007).

Table 2 ***Terms of Reference for subreviews***

Optical review (NR)	SAR review (Norut)
Den nasjonale snøtjenesten for Norge driftes av NVE og METNO og omfatter tjenester av typen Snøkart for Norge (se http://www.nve.no/snokart og http://MET.NO/snokart). Vi starter nå et arbeid for å forbedre den nasjonale snøtjenesten ved å forbedre de satellittbaserte snøtjenestene. Aktuelle satellittbaserte sensorer er MODIS, AVHRR (på sikt VIIRS), Radarsat(1/2) ScanSAR. Envisats MERIS og ASAR (ScanSAR modus) er også aktuelle sensorer under forutsetning at de blir operasjonalisert. Arbeidet gjøres i prosjektet CryoRisk. Norsk Regnesentral deltar og har tidligere deltatt i flere nasjonale og internasjonale prosjekter der målet har vært utvikling av snøkartleggingsrutiner. I CryoRisk ønsker vi, der det er relevant, å bygge på dette arbeidet. I arbeidet med å forbedre den nasjonale snøtjenesten ønsker vi at Norsk Regnesentral bidrar med en gjennomgang av eksisterende automatiske snøkartleggingsrutiner for optiske instrumenter. Dette vil inngå i en kost/nytte analyse der målet er å bestemme hvilke algoritmer som protoypes og deretter implementeres. Bidraget må dekke: 1) En gjennomgang av eksisterende	Den nasjonale snøtjenesten for Norge driftes av NVE og METNO og omfatter tjenester av typen Snøkart for Norge (se http://www.nve.no/snokart og http://MET.NO/snokart). Vi starter nå et arbeid for å forbedre den nasjonale snøtjenesten ved å forbedre de satellittbaserte snøtjenestene. Aktuelle satellittbaserte sensorer er MODIS, AVHRR (på sikt VIIRS) og Radarsat(1/2) ScanSAR. Envisats MERIS og ASAR (ScanSAR-modus) er også aktuelle sensorer under forutsetning at de blir operasjonalisert. Arbeidet gjøres i prosjektet CryoRisk. Norut IT deltar og har tidligere deltatt i flere nasjonale og internasjonale prosjekter der målet har vært utvikling av snøkartleggingsrutiner med bruk av SAR-sensorer. I CryoRisk ønsker vi, der det er relevant, å bygge på dette arbeidet. I arbeidet med å forbedre den nasjonale snøtjenesten ønsker vi at Norut IT bidrar med en gjennomgang av eksisterende automatiske snøkartleggingsrutiner for SAR-sensorer (ScanSAR-modus). Dette vil inngå i en kost/nytte analyse der målet er å bestemme hvilke algoritmer som protoypes og deretter

automatiske optiske algoritmer for snøkartlegging, herunder Norsk Regnesentrals algoritme. Algoritmene skal beskrives i detalj, evt. vha offentlig tilgjengelige referanser. 2) En detaljert beskrivelse av relevante skydeteksjonsalgoritmer og anbefalt valg av algoritme knyttet til snødeteksjonsalgoritmer der dette ikke er implisitt. 3) En vurdering av styrker og svakheter ved de ulike algoritmene/algoritmekombinasjonene. 4) Det må tas hensyn til at algoritmene skal brukes under norske forhold. Det erkjennes at ikke alle algoritmene er testet ut på det samme datasett og at det dermed kan være vanskelig å gjøre en objektiv sammenlikning.	implementeres. Bidraget må dekke: 1) En gjennomgang av eksisterende automatiske algoritmer for snøkartlegging med SAR (ScanSAR-modus). Algoritmene skal beskrives i detalj, evt. vha offentlig tilgjengelige referanser. 2) En detaljert beskrivelse av Norut IT sin SAR-algoritme (ScanSAR-modus). 3) En beskrivelse av styrker og svakheter for de forskjellige SAR-snøalgorimer.

The reviews provided valuable information on the current opportunities, limitations and usefulnes of snow and partly clouds algorithms. The main conclusions are listed in Table 3.

Table 3 ***Summary of reviews***

Optical review (NR)	SAR review (Norut)
Snow monitoring is possible using optical sensors and a number of algorithm types are reviewed: clustering algorithms and maximum likelihood algorithms for classifying a pixel into snow or no snow (e.g. ISODATA, thresholding of NDSI), and fractional snow cover algorithms (NLR, NDSI, spectral unmixing, spectral BRDF assimilation). The NLR algorithm is similar to the manual algorithm in use by NVE (Schjødt-Osmo and Engeset, 1997). The NLR-type algorithm has these pros and cons: + easy to implement + good results in general – no data under clouds, problems with cloud shadows and thin clouds	Snow monitoring is possible using SAR and two algorithms reviewed: Nagler-algorithm and HUT-algorithm. The HUT-algorithm is regarded as not suitable for Norway, as the requirements are unfeasible to meet (i.e. a reference scene acquired exactly at the start of the melting point and detailed inventories of stem volumes). The Nagler-algorithm has these pros and cons: + easy to implement + good results during the melt period + no cloud interference – need reference image with dry snow & ground for each acquisition geometry to be

– underestimates snow covered area, especially at low sun angles (during winter due to shadows), at north-facing slopes, and at end of melt season (dirty snow surface) Spectral unmixing algorithms were presented, but no ready-to-implement algorithm was recommended. NDSI is implemented by NASA and assessed as comparable to, or less accurate than NLR. NR is working on a new algorithm based on spectral BRDF assimilation. The algorithm is promising but requires further work to be considered for operationalisation. One algorithm (K-NN) only is reviewed for cloud cover detection using MODIS. As compared with the NASA cloud algorithm this works generally marginally better.	used – maps wet snow only – problems in steep terrain and forest – underestimating patchy snow cover due to non-linear relationship between snow cover fraction and backscatter – dry snow cannot be mapped directly

4.2 Optical

4.2.1 Background

Using optical sensors several different approaches can be used to infer cloud cover and /or snow cover from satellite data. Existing cloud mask/classification schemes can be categorised as either syntactic (physical threshold classification) or statistical (decision theory) classification.

Syntactic algorithms usually provide information on cloud/no cloud and subsequently snow/no snow on the cloud free pixels, while the statistical algorithms sometimes produce a probability of the various classes (e.g. cloud, snow, cloud free and no snow). Most operational schemes, e.g. NWCSAF PPS, MAIA, Apollo, CLAVR, IMAPP (e.g. Derrien et al., 1993, Dybbroe et al., 2005a, 2005b, Stowe et al., 1999) are syntactic. These are typically based upon thresholds defined in multidimensional feature space. Whether thresholds are based upon statistics or dynamically adapted using RTMs and NWP input varies. A schematic presentation of threshold based algorithms is given in Figure 6 and some samples are given in Figure 7 and Figure 8.

Concerning statistical classification algorithms, we are currently not aware of any operational systems in use at any meteorological or similar institutions. At the UK Meteorological Office, a neural network approach has been operational, but this is more of a syntactic algorithm than a statistical algorithm. Within the Eumetsat OSISAF project a statistical algorithm, including both cloud mask and snow ice detetction, has been developed for identification of sea ice in AVHRR imagery (Breivik et al., 2001). A

sample product from the Bayesian algorithm developed at METNO is presented in Figure 9.

Solberg et al. (2006) present a review of several optical algorithms for snow cover extraction and one cloud mask algorithm. The main focus of the report is the presentation and evaluation of optical snow algorithms at Norwegian Computing Center (NR), less focus is given to the preceding step of determining whether a pixel is cloud covered, contaminated or clear.

4.2.2 Syntactic algorithms discriminating both clouds and snow

METNO has long experience in developing and using syntactical algorithms of the type listed above (Godøy and Sunde, 1996, Godøy and Sunde, 1997, Godøy and Eastwood, 2002). Starting in 1994, METNO developed an algorithm similar to SCANDIA, but which focused at cumuli- and stratiform clouds, height level of clouds, fog, and snow instead of cloud types. This algorithm is however sleeping due to the combined European efforts through the EUMETSAT NWCSAF work.

Starting with APOLLO (Saunders and Kriebel, 1988), SCANDIA (Karlsson and Liljas, 1990), MAIA (Derrien et al., 1993, Derrien and LeGleau, 2005) and CLAVR (Stowe et al., 1999) syntactic algorithms were implemented in an operational suite at various meteorological institutes in Europe and the US. Common to these were the use of threshold values in a multi dimensional feature space where the thresholds were set using extensive training data reflecting various surfaces, atmospheric conditions and observation geometry. The approach used within these algorithms is still used in more modern algorithms such as EUMETSAT SAF in Support of Nowcasting and very short range forecasting (NWCSAF) Polar Platform System (PPS, Dybbroe et al., 2005a, b). This algorithm has replaced APOLLO and to a large extent SCANDIA which is now being used only for mesoscale analysis and climatological purposes.

The CLAVR algorithm is a pure cloud masking algorithm and does not provide snow cover.

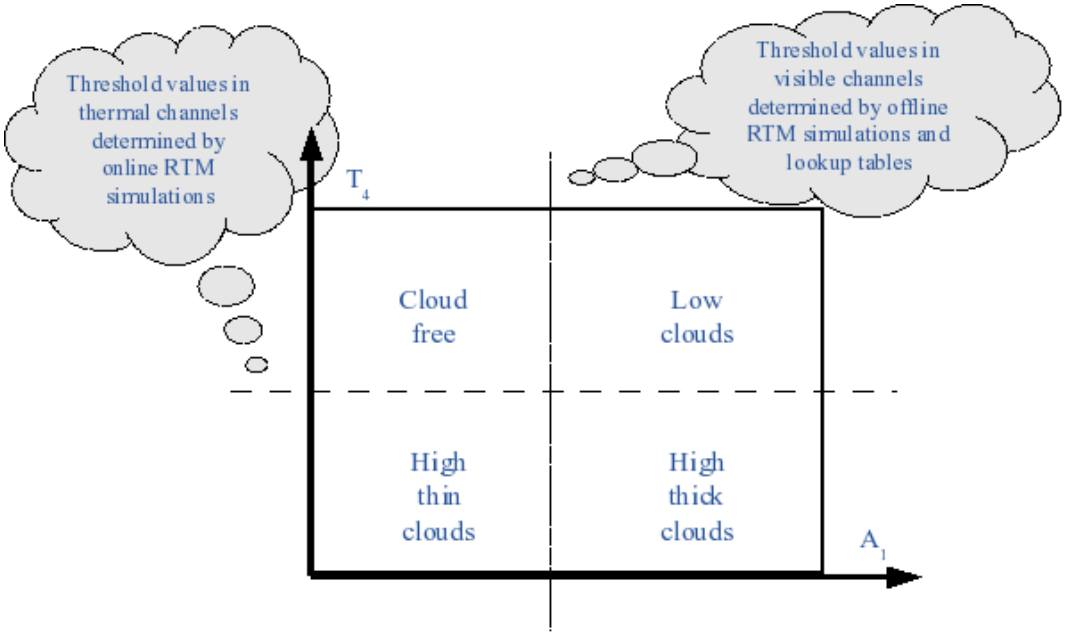


Figure 6 Schematic presentation of syntactic or threshold based method for cloud and snow discrimination. In this illustration the brightness temperature of AVHRR channel 4 (11.5 µm) and bi-directional reflectance of AVHRR channel 1 (0.6 µm) are used.

Within the meteorological community in Europe today it is generally MAIA (Derrien et al., 1993, Derrien and LeGleau, 2005) and NWCSAF PPS that is being used operationally. Both perform cloud and sea ice/snow screening. The two publications describing MAIA are separated by some time, and the later one (Derrien and LeGleau, 2005) actually describes the NWCSAF MSG algorithm, but this is similar to MAIA. Both algorithms have been thoroughly tested and validated under global conditions over the last years (e.g. Godøy, 2005, Lavanant et al., 2006). In Godøy (2005) NWCSAF PPS was validated against Norwegian synop stations with manual reports of cloud and snow cover. Lavanant et al., 2006 compared both NWCSAF PPS and MAIA to an extensive dataset covering more than 18000 sea and land targets with about 10000 oceanic targets. About 15% of the data were night time data and 5% twilight. The performance of both these algorithms is quite good in general, but both have had some trouble using 3.7 µm for sea ice detection and detection of semi-transparent cirrus clouds over sea ice. During the validation process described in Lavanant et al. (2005) several weaknesses was identified in both schemes, but these were corrected, and the points raised above are now the remaining main problems.

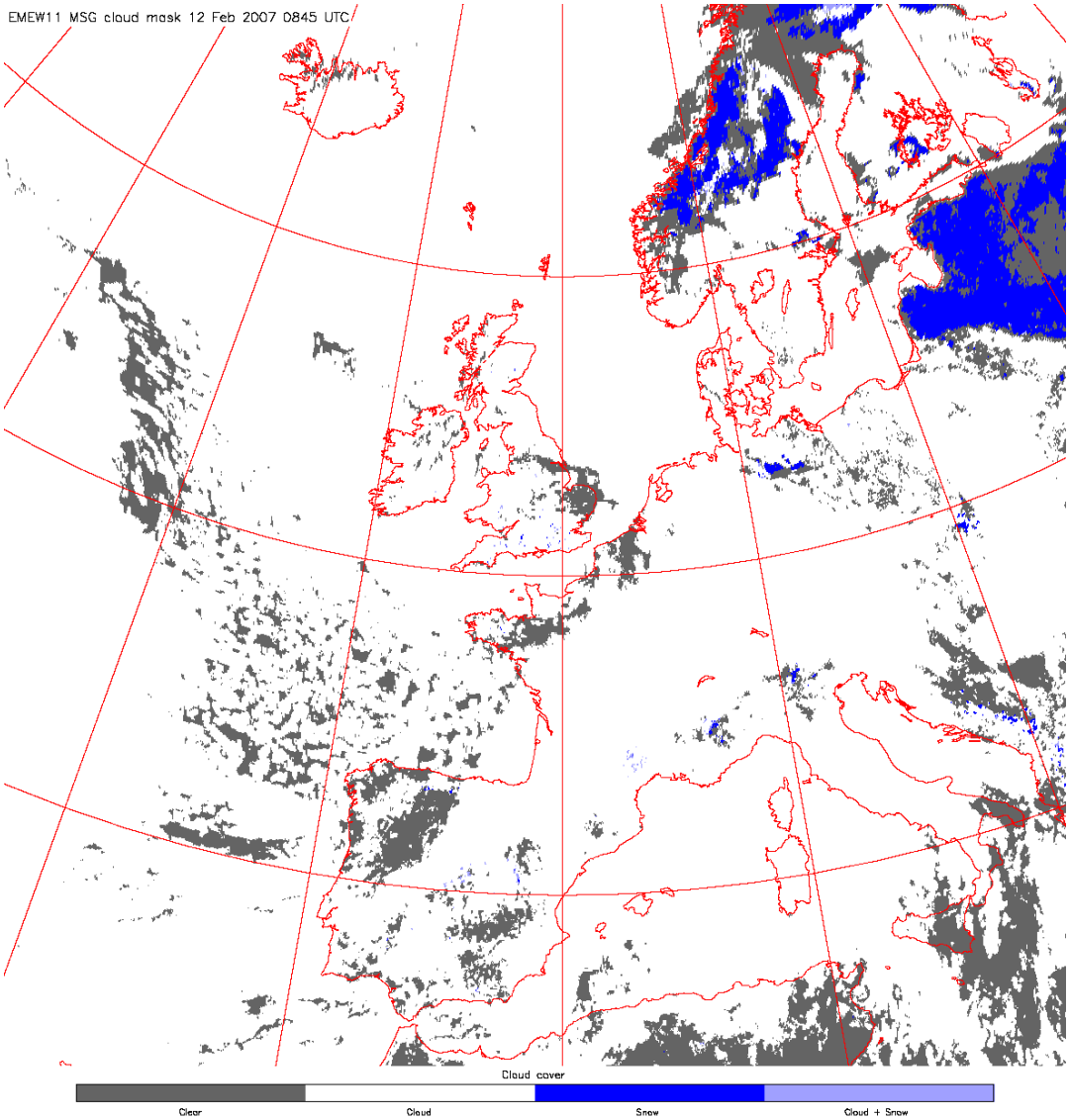


Figure 7 NWCSAF MSG snow cover product from UK Meteorological Office (Courtesy of UKMO and Roger Saunders).

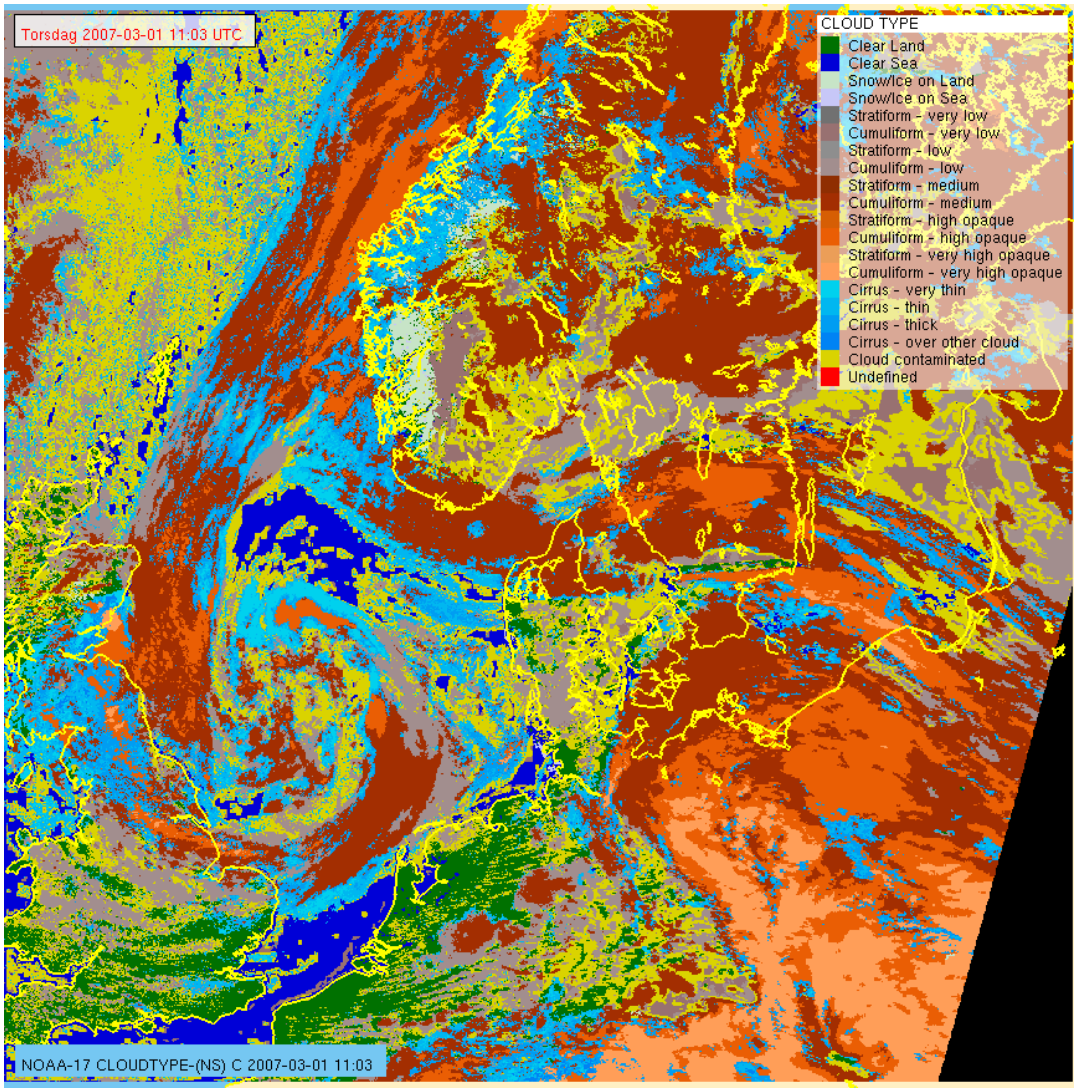


Figure 8 Sample product of NWCSAF PPS processed scene, including cloud types and snow and sea ice.

4.2.3 Statistical algorithms discriminating both clouds and snow

Within the EUMETSAT Ocean and Sea Ice SAF and EU EuroClim projects, METNO has achieved knowledge in using the Bayesian approach both on microwave and optical sensors, as well as in combining the various sensor-based products into a multi-sensor product. Concerning the extraction of sea ice information from AVHRR data, a Bayesian algorithm has been developed. This is based upon the collection of training data over various surfaces. It divides each image into three classes: clouds; clear; and clear and covered by sea ice. This algorithm has also been tested over land with promising results (Figure 9).

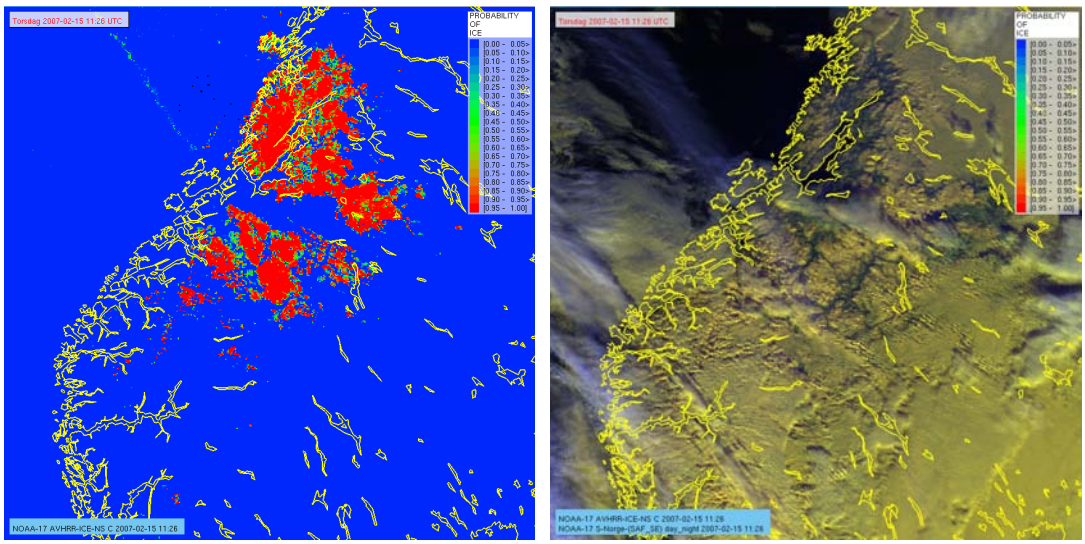


Figure 9 Bayesian product, left panel shows probability of the pixel being snow, right panel shows the RGB composite of AVHRR channels representing 0.6, 0.9 and 11.5.

The basic principle of the algorithm is described in Eq 1. I_k represents independent classes, while A_n represents the spectral features being used.

$$p(I_k \mid A_1,\ldots,A_n) = \frac{p(A_1 \mid I_k)\cdot p(A_2 \mid I_k)\cdot\ldots\cdot p(A_n \mid I_k)\cdot P(I_k)}{\sum_j p(A_1 \mid I_j)P(I_j)\cdot\ldots\cdot p(A_n \mid I_j)P(I_j)} \qquad \textbf{Eq 1}$$

To visualise the procedure, the probability density functions of the ratio of 0.9µm and 0.6µm, and 1.6µm and 0.6µm are shown in Figure 10. The training data used to develop these probability density functions were collected during the OSISAF project and have open water, clouds and sea ice as classes. These features are extensively used in operational cloud and snow screening.

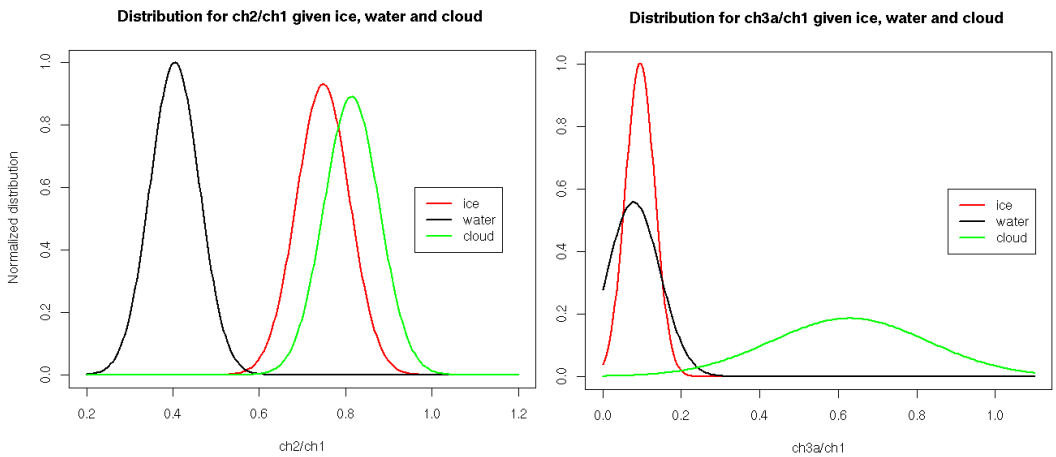


Figure 10 Probability density functions for the ratio of 0.9µm and 0.6µm (left), and 1.6µm and 0.6µm (right). These results have been obtained for sea ice classification.

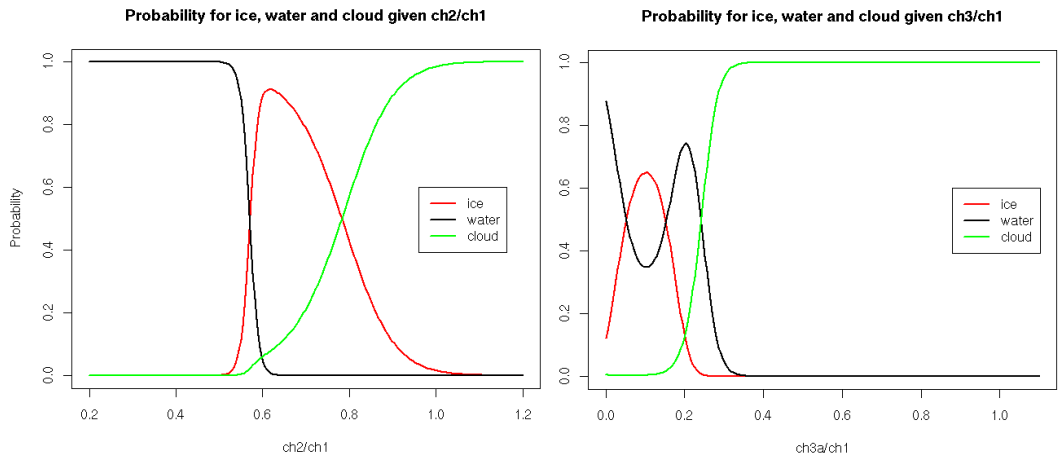


Figure 11 The resulting classification when using only one feature in the Bayesian approach. These results have been obtained for sea ice classification.

By implementing the probability density functions of Figure 10 in Eq 1, the results presented in Figure 11 are achieved. The regions with overlapping probability density functions for the three classes involved are clearly observed. In these regions the algorithm reflects the uncertainty in the classification. By adding more spectral features, the uncertainty of the algorithm is reduced, although not completely removed. The experience of the tests performed over land so far is that the major problem of the algorithm is cloud shadows where the uncertainty in the classification is not reflected in the probabilities. Furthermore, the present version of the algorithm works well for discovering snow in open areas, but needs to be adopted for boreal areas. This will be done using experience gained at METNO through the EuroClim project. This has to be improved. It is expected that increasing the training data to get more representative data for all observation geometry configurations will improve the algorithm. When these modifications are implemented the main potential lies in atmospheric correction of the spectral features, although this is expected to give less impact at high latitudes than at lower latitudes.

To our knowledge, there is no other statistically based algorithm that does both cloud and snow screening, and that is operationally or semi-operationally used at present (at least within the meteorological community).

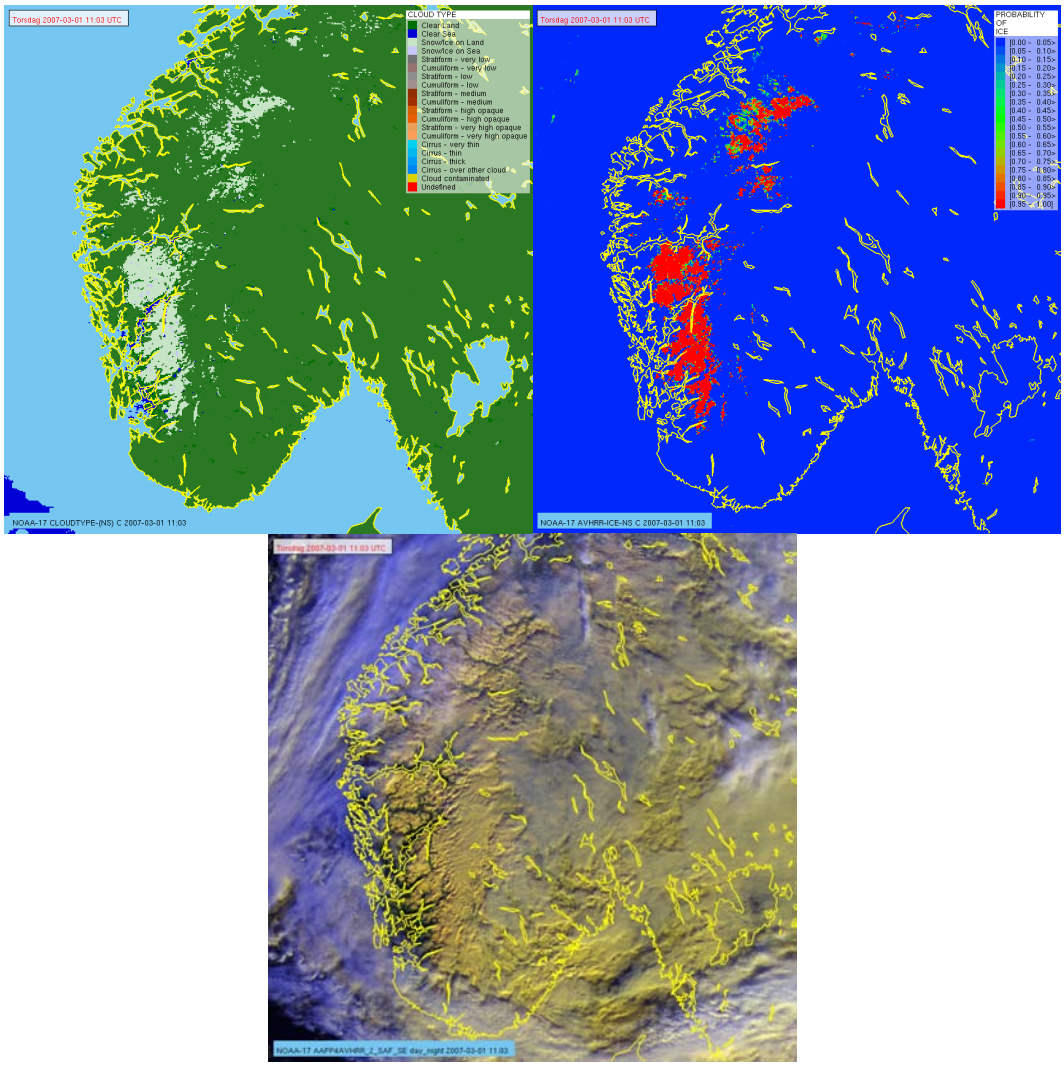


Figure 12 Comparison of snow results from the NWCSAF PPS software and the Bayes classification for a scene covering southern Norway on March 11:03 UTC, 2007. The top panel shows the NWCSAF PPS results to the left and the Bayes results to right. The bottom panel shows the RGB composite of AVHRR channels 1, 2 and 4 for visual interpretation. The NWCSAF PPS output has been modified to emphasise the snow by excluding the cloud classes. Thus, green areas are not necessarily clear.

A comparison of the results gained by using the NWCSAF PPS software and the Bayes approach on the same scene is presented in Figure 12 along with the RGB composite of AVHRR channels 1, 2 and 4. The NWCSAF PPS results have been modified in presentation, by excluding the cloud classes and keeping only the snow and sea ice classes for better comparison with the Bayes results. Concerning the Bayes results, the illustration presented shows only the probability of snow/sea ice, no selection of classes by selecting the class (cloud, snow/sea ice, cloud free) of highest probability has been done. The results achieved are very similar and these methods will be compared throughout the spring. The NWCSAF PPS software can be regarded as the fallback algorithm of the CryoRisk project for both AVHRR and MODIS interpretation as this software is already capable of processing MODIS data through a pre-processing step. However, given the subsequent analysis step when remote sensing products are to be integrated with other data (e.g. in situ data) the Bayes approach is considered favourable from the point of view of METNO.

The present implementation of the Bayes approach has some insufficiencies which will be addressed through the CryoRisk project, The use of Markov Random Fields (MRF) using class labels in combination with Bayes classification will be examined and evaluated in terms of cost-benefit. A brief introduction is given below. To simplify the notation we show it for only the one-dimensional case as given in Eq 2.

$$p(I_k \mid A_1) = \frac{p(A_1 \mid I_k)p(I_k)}{\sum_j p(A_1 \mid I_j)P(I_j)} \qquad \textbf{Eq 2}$$

In this combination with MRF, the $p(I_k)$ is called the spatial model and models the correlation between class labels for all pixels in the image. If $p(I_k)$ has no contextual meaning, $p(I_k)$ is considered the a priori part of the Bayesian classification rule.

A constraint is given which states that for a Markov field I_k, the conditional distribution of a pixel in the field given all other pixels are only dependent of it neighbors:

$$p(I_k(i,j) \mid I_k(k,l); k,l \neq i,j) = p(I_k(i,j) \mid I_k(k,l); k,l \in \Re_{i,j}) \qquad \textbf{Eq 3}$$

$\Re_{i,j}$ is the local neighborhood around pixel (i,j) and $k,l \neq i,j$ refers to all pixels in I_k with the exception of (i,j). Figure 13 gives an illustration of the local neighborhood defined by Eq 3.

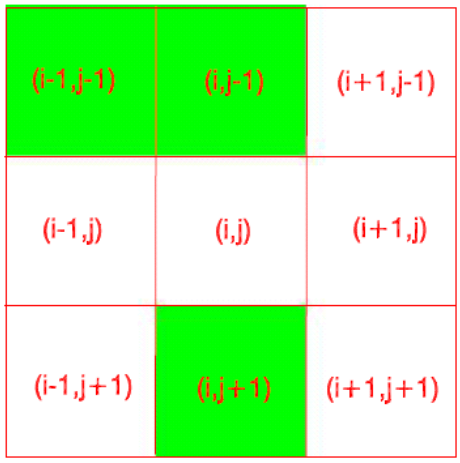


Figure 13 Illustration of the local pixel neighbourhood of pixel (I,j) with class labels (green are bare ground and white snow labels).

According to the Hammersley-Clifford theorem (Dubes and Anil, 1989) $p(I_k)$ can be expressed as a Gibbs potential field having probability function given in Eq 4.

$$p(I_k(i,j)) = \frac{1}{Z} e^{-U(I_k(i,j))/T} \qquad \textbf{Eq 4}$$

A common model for $U(I_k(i,j))$ from Eq 4 is the Ising model given in Eq 5.

$$U(I_k(i,j) = \beta \sum_{\{k,l\} \in \Re_{i,j}} I(I_k(i,j), I_k(k,l))$$

$$I(I_k(i,j), I_k(k,l) = \begin{cases} -1 \rightarrow if \rightarrow I_k(i,j) = I_k(k,l) \\ 0 \rightarrow if \rightarrow I_k(i,j) \neq I_k(k,l) \end{cases}$$

Eq 5

The function $U(I_k(i,j))$ actually counts the number of pixels in the neighbourhood $\Re_{i,j}$ which have the same class label as $I_k(i,j)$. β is a weighting parameter. This use of MRF can be seen as a form of spatial smoothing of the resulting image with regard to the dominant class label in the neighborhood. The Z and T in Eq 4 can be ignored as Z is a normalising coefficient and T is temperature. When using MRF in a classification context these coefficients could be set to 1 and ignored.

The conditional likelihood function $p(A_1 \mid I_k)$ and the a priori $p(I_k)$ in Eq 2 can be used by applying Bayes classification rule using the MAP criteria.

$$\begin{aligned} I_{k,MAP} &= \arg\max p(I_k \mid A_1) = \arg\max p(A_1 \mid I_k) p(I_k) \\ &= \arg\min\{-\ln p(A_1 \mid I_k) + \ln p(I_k)\} \\ &= \arg\min\left\{ -\ln p(A_1 \mid I_k) + \beta \sum_{\{k,l\} \in \Re_{i,j}} I(I_k(i,j), I_k(k,l)) \right\} \end{aligned}$$

Eq 6

We will use a sub-optimal method named Iterated Conditional Mode (ICM) to solve the classification scheme in Eq 6. Some modifications are required when using ICM. Eq 7 states that all pixel values in image A_1 are class-conditional independent. This is a requirement for using ICM.

$$p(A_1 \mid I_k) = \prod_{\{i,j\} \in \{k,l\}} p(A_1(i,j) \mid I_k(i,j))$$

Eq 7

The ICM algorithm is defined as follows:

1. Initialize A_1 for each pixel in the image to the class label which minimises the non-contextual function. This is equivalent to using Bayes classification rule.
2. For all pixels, update A_1 with class labels which minimise Eq 6.
3. Repeat step 2 N times until a convergence is reached.

Generally, 5-6 iterations are enough to stabilise the solution.

Above, a brief description of how to use spatial relationships in combination with Bayes classification rule is given. This approach could also be extended to support temporal relationship by extending the function given in Eq 5 with a temporal part.

$$U(I_k(i,j) = U_{spatial}(I_k(i,j)) + U_{temporal}(I_k(i,j)) \quad \text{Eq 8}$$

The temporal part of Eq 8 could be modelled as a Markov chain where transition probabilities between class labels are modelled. Storvik et al. (2002) gives a framework based on spatial and temporal modeling using MRF in combination with EO data.

4.2.4 Snow discrimination algorithms and sub pixel algorithms

The Finnish Enviroment Institute (SYKE) provides daily snow cover products (see http://www.environment.fi/default.asp?contentid=213551&lan=EN, and Metsämäki et al., 2005) based upon Terra/MODIS data. They use a semi empirical reflectance model where the reflectance of the target is expressed as a function of the snow covered area. There is no clear presentation of the cloud mask used.

Solberg et al. (2006) describe the snow cover algorithms of Norwegian Computing Center and the cloud mask prototype they have been using together with the snow cover extraction for MODIS data. The cloud mask is based upon a K Nearest Neighbor classification, more commonly known as cluster analysis within the meteorological community. We are currently not aware of anybody running such a service operationally (at least within the meteorological community).

NR's new optical snow cover algorithm (Solberg et al., 2006) is built on spectral unmixing. The spectral bidirectional reflectance distribution function (BRDF) characteristics of the snow and bare ground are modelled locally, pixel by pixel. Linear spectral unmixing is then applied to estimate the current snow fraction per pixel.

The Norwegian linear reflectance-to-snow-cover (NLR) algorithm described in Solberg et al. (2006) is based on mapping the reflectance in one band to fractional snow cover ranging from 0 – 100 %. The model is calibrated by providing two values initialising the 0 and 100 % reflectances.

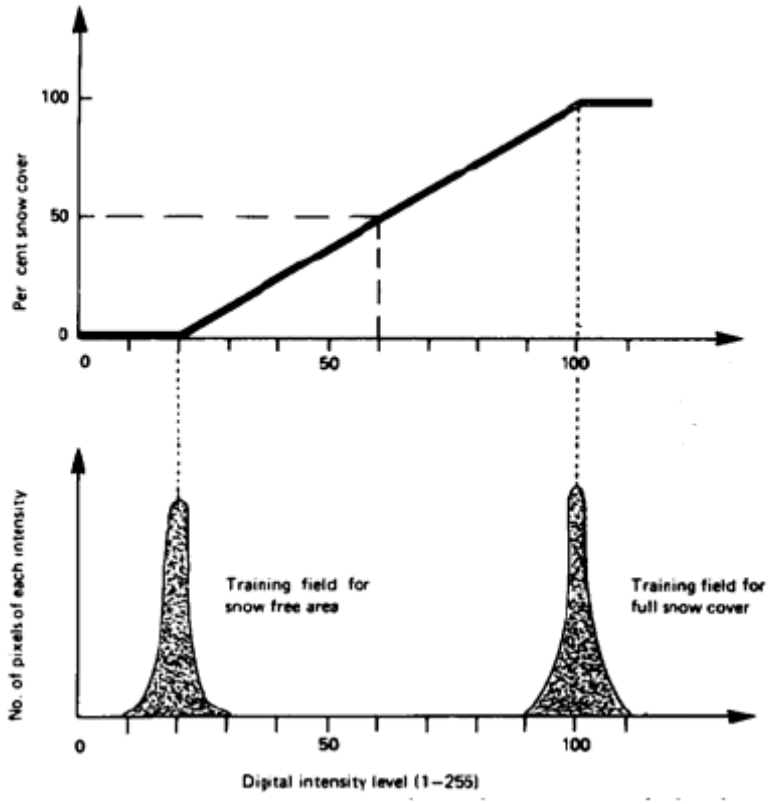


Figure 14 The NLR algorithm illustrated (Andersen, 1982).

The Normalized Difference Snow Index (NDSI) given in Eq 9 is what NASAs SNOWMAP algorithm (Hall et. al, 2002) is based upon. A relationship between NDSI and snow cover has been established by using Landsat TM images and it was found that a pixel has more than 50 % snow when NDSI >0.4 (Hall et al., 2001). A detailed description of the SNOWMAP algorithm can be located at http://modis-snow-ice.gsfc.nasa.gov.

$$NDSI = \frac{band(0.55\mu) - band(1.62\mu)}{band(0.55\mu) + band(1.62\mu)} \qquad \textbf{Eq 9}$$

Salomonson et al. (2004, 2006) has recently extended the SNOWMAP algorithm to support fractional snow cover. This is done by developing a regression relationship between fractional snow cover and NDSI for MODIS sensors.

Within the EnviSnow project a modified version of the SNOWMAP algorithm was proposed and applied to MODIS data in Alpine regions (Malcher and Rott, 2004). This version also tried to use the NDSI to separate snow covered pixels into fractional snow covered pixels with two classes (70% and 100%), but achieved mixed results.

4.2.5 Open water classification

Due to significant differences in surface roughness of various type of land (land, snow on frozen lakes, glaciers, forest etc) the spectral signature will responds differently in time and space. The images should therefore be masked for various land types. For OWS study the mask should remove all the pixels that do not belong to the water classes.

A snow-free newly frozen lake often appears dark in the visible band and can be difficult to distinguish from open water. Consequently, there can be problems in identifying the timing of initial ice formation with visible band data. It is possible to discriminate between open water and ice on large lakes with passive microwave. Passive microwave images can not be used due to the relatively low satellite resolution. Most lakes in Norway have an area of less than 10 km^2. On large lakes, a considerable thickness of ice is required to resist wind forces without breaking, and initial ice cover formation is much more dynamic than on small lakes. It will therefore take time for he whole lake to freez and in some years only part of the lakes will be frozen. Fracturing, movement and refreezing of the ice cover during the freeze-up event may cause difference in reflectance and is thus detectable from optical satellites. When snow starts to accumulate on the lake ice it should be possible to distinguish it from open water with optical satellites. There could be several weeks offset between the formation of lake ice and the time of first snow on the ice. The exact time of freeze-up could not be determined. Similarly, it may be difficult to determine the exact time of break-up. Lake ice break-up begins when the snow cover starts to melt but the lake ice seldom disappears before the snow has completely melted. Snow ice or lake ice will then be exposed and the albedo decreases. However, it could be difficult to discriminate between open water and ice. We will use the snow product (snow classification) described earlier together with a lake ice mask to determine OWS vs frozen lakes.

4.2.6 Rivers

We do not expect much information on rivers since Norwegian rivers are relatively small compared with the satellite resolution, where AVHRR has 1 km resolution and MODIS has 500 or 250 m resolution for the channel planned to be used. However, some initial studies have shown promising results using the satellite derived snow maps for simply mapping the presence or absence of ice. The break-up of river ice is controlled by both thermodynamic/hydrothermal and dynamic/hydrodynamic processes (Prowse, 1994, 1995). Therefore the river ice will often break-up before all the snow has melted from the ice surface. Because the contrast in spectral signature between snow covered river ice and open water is large it should be possible to monitor break-up in larger rivers (e.g. Pavelsky and Smith, 2004). We will therefore use the snow product (snow classification) described earlier together with a river/lake ice mask to determine break-up patterns/timing.

4.3 SAR

4.3.1 Snow classification

SAR satellites presently are limited to the C-band (5.6 GHz). The radar signal in this band isn't affected by clouds as are optical sensors. This is a great advantage when it comes to monitoring snow covered areas, but there are some drawbacks. The C-band is capable at detecting wet snow only. The sensitivity to dry snow is very low. This has led to an alternative way of detecting snow cover area where the wet snow results are combined with a height model (DEM) to infer dry snow (Nagler and Rott, 2000, Malnes, 2007). This method has its drawbacks as the area of dry snow will contribute 100 % to the total snow cover area. This will usually overestimate the snow cover for dry snow, as it seems likely that parts of the terrain with steep slopes and those parts which are facing south may be snow-free.

The most common way to classify wet snow from SAR is to take the difference in dB between an acquired image and a reference image taken under snow free or dry snow conditions (Baghdadi et al., 1999, Nagler and Rott, 2000). This method uses the idea that wet snow has low backscattering compared with dry snow and bare ground which have strong backscattering. This is valid only when the area is not forested, as these will contribute to the backscattering even if the snow is wet and reduce the difference between bare ground/dry snow and wet snow. This will reduce the performance of the algorithm when detecting wet snow. The algorithm is usable only for areas without forest. The difference in dB approach eliminates the topography which affects the backscattering. The Nagler wet snow algorithm (Nagler and Rott, 2000) describes a scheme as given above where a pixel is classified as wet snow if the difference is less than -3dB. Figure 15 gives an illustration of the Nagler algorithm.

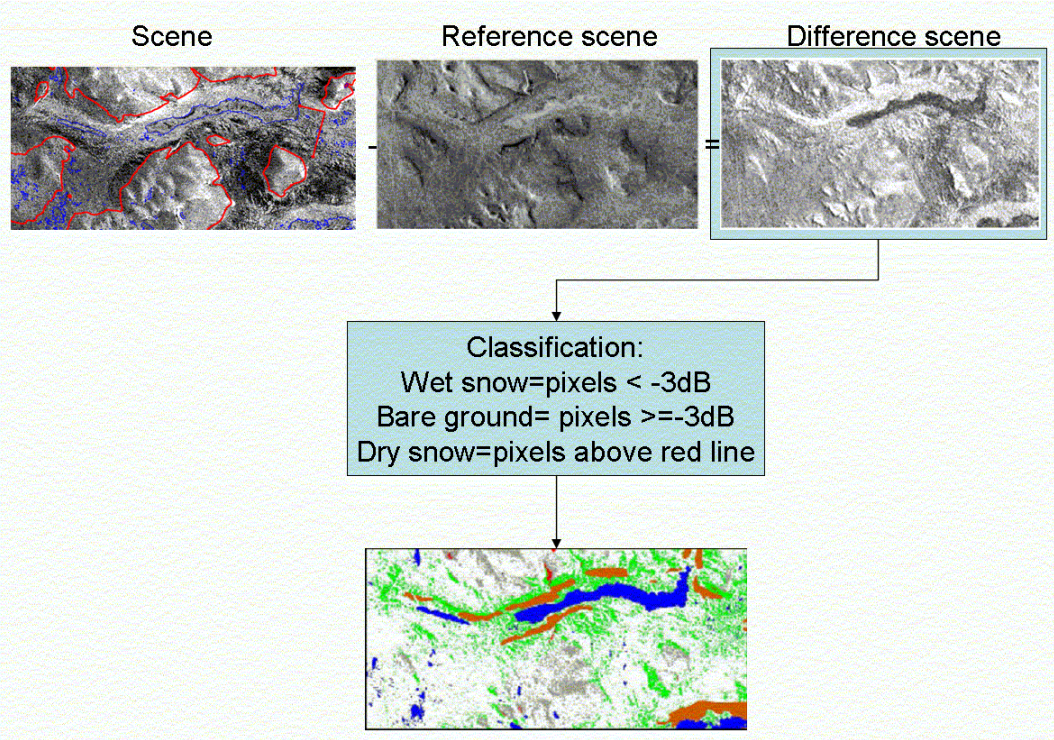


Figure 15 Illustration of the Nagler algorithm and how dry snow can be inferred.

A drawback with this approach is that it might be difficult to acquire good reference images. The reference images must also be in the same satellite geometry (viewing angle) as the image which it is being used with. Malnes (2007) describes in detail Norut IT implementation of the Nagler algorithm.

4.3.2 Open water classification

Due to significant differences in surface roughness of various type of land (land, snow on frozen lakes, glaciers, forest etc) the backscatter coefficient responds differently in time and space. The images should therefore be masked for various land types. For OWS study the mask should remove all the pixels that do not belong to the water classes.

When lakes freeze and become completely ice covered, the backscatter is low due to specular reflection away from the radar of the relatively smooth upper and lower surfaces of the ice. However deformation features, such as cracks or ridging/rafting features that developed as the wind fractured and displaced the thin ice cover during the ice formation period, will intensify the backscatter. Backscatter intensity from deformation features is strong compared with that of the adjacent ice cover at the beginning of the ice growth period (Morris et al. 1995). As the ice cover thickens there is an increase in backscatter due to the combined effects of reflection off the ice-water interface and forward scattering from bubble inclusions and from slush (wet snow). Further, a frozen lake will be covered by snow on top of the ice during the winter, and the backscatter increases compared with that of open water.

When the snow becomes wet due to either surface melting or flooding the backscattering reduces to about the same level as for open water (Malnes and Guneriussen, 2002). Flooding and snow ice formation occur when the mass of snow is sufficient to overcome

the buoyancy of the ice and depress the ice surface below water level; fractures present allow water to flow up to the ice surface and wet the snow cover, and the resulting slush freezes. Where melting snow cover is present, the absorption of the radar signal will reduce the backscatter. Melting will result in snow free ice, with relatively high backscattering. However the backscatter could be low due to an increase in specular reflection away from the radar receiver, resulting from internal melting of the ice and pounding of water. The detection of ice break-up can therefore sometimes be difficult with radar when the surface become wet (pounding and/or wet snow) (Hall et al, 1994 and Duguay et al., 2002). Thus, break-up dates may best be detected using both optical and SAR data.

However, when all the ice vanishes and the backscattering from open water is low, the differences in surface roughness may cause significant temporal changes of backscattering coefficient. This change in surface roughness is due mainly to wind action on the lake surface. When the lakes are frozen a more stable backscattering coefficient will be expected. Large temporal change in backscatter may thus be used as an open water indicator.

Satellite synthetic aperture radar (SAR) imagery in particular has been shown to yield cost-effective information on ice type on medium and large rivers (i.e. more than 100 m wide) in an operational context. Autumn ice jams can be identified in SAR images because deformation creates rough surface that cause strong backscatter and bright signatures for months after their initial formation (Melloh and Gatto, 1990, a, b, c, 1992). Similarly, winter and spring cracks/ice jams could be detected by SAR.

4.4 Multi sensor

The work of NR and Norut IT in the EnviSnow project regarding fusion of SAR and optical snow cover was based on a confidence level for each pixel. The confidence ranged from 0 to 100 where 0 meant no SCA observed. The confidence function for optical pixels is a product of pixel sample ground size, cloud probability and snow age. The function for SAR pixels included classification confidence (distance to threshold), acquisition geometry, air temperature in reference and classified SAR scenes.

METNO have experience in combining different sensors through the EUMETSAT OSISAF project. Within this project the Bayes approach has been used to combine different sensors (SSM/I, Scatterometer and in the future possibly AVHRR) for sea ice detection, while an approach using confidence levels has been adopted for combining radiative flux products generated from the geostationary SEVERI and polar orbiting AVHRR instruments. The confidence levels depended on the observation geometry, confidence levels of the cloud type product (NWCSAF PPS), information on sea ice and internal processing conditions. Both approaches will be considered for CryoRisk. If Bayes is to be used for the multi-sensor product, it is necessary that the SAR algorithm provides information in a form that allows this procedure.

5 Selection of algorithms

It is the experience of METNO that much of the error in snow cover detection using optical algorithms can be attributed to the cloud discrimination process. This is due to the similar radiometric signature of snow/sea ice and clouds. Whether using an integrated algorithm which performs both cloud and snow screening or using a combination of algorithms, one for cloud discrimination and one for snow discrimination, it is useful to also validate the combined result of these and not validate them separately. The main reason for this is that errors in the cloud discrimination will affect the validation of the snow discrimination.

Given the operational requirements at METNO and the similar radiometric signatures of clouds and snow, it is beneficial from the point of view of METNO that an integrated algorithm is selected. The mandate of the project is to establish an operational service, and the operational experience within this field at other meteorological institutes in Europe favours simple and rather robust algorithms for this use. The NWCSAF PPS would be the first choice for the fallback algorithm as this can also run on MODIS data. However, given the experience achieved through OSISAF efforts and the use of remote sensing products within an analysis scheme, the Bayes approach is both tempting and promising. It will however, need some adaptation over land (especially over boreal surfaces). The Bayes approach would be consistent with the operational service for sea ice and cost-effective to tune and operate through well known interfaces.

As the primary interest for NVE is sub-pixel information regarding snow cover, NVE will continue to use the NLR-algorithm, but the cloud mask will be delivered from METNO (given that METNO processes the requested sensor). Further use of the Bayesian classification scheme METNO is developing would be interesting for NVE if a relationship between probabilities given by the scheme could be connected to fractional snow cover. Also the ability to model the temporal relationship via the Bayes classification rule using Markov random fields makes this approach interesting for NVE.

The SNOWMAP product, which includes the fractional snow cover product along with cloud mask delivered from NASA/NSIDC will be downloaded for use and comparison with our own results.

The algorithm selected when using SAR images is the Nagler algorithm as described by SAR algorithm review report (Malnes, 2007).

Algorithm selection regarding open water classification with SAR data will be based on trying several algorithms. Unsupervised classification algorithm will be tested on OWS classification. This will be done using ISODATA and K-means algorithms over water bodies constrained using GIS data (water and river boundaries). The effect of local incidence angle can probably be neglected due to the lakes relatively small area. Manual post-processing of the segmentation done by the unsupervised algorithms is needed to label the classes correctly.

Algorithms for OWS when using optical sensors will be based on the same algorithms used by the snow cover algorithms.

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