Multi-sensor and time-series approaches for monitoring of snow parameters

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***Abstract*—Frequent mapping of snow parameters, like snow cover area (SCA) and snow surface wetness (SSW), is important for applications in hydrology, meteorology and climatology. In this study we have developed a few general multi-sensor/time-series approaches for such monitoring. The objective is to analyze, on a daily basis, a time series of optical and Synthetic Aperture Radar (SAR) data together producing sensor-independent products. A few algorithms for multi-sensor/time-series processing have been developed and are compared in this study. A typical approach is to analyze each image individually and combine them into a day product. How each image contributes to the day products is controlled by a pixel-by-pixel confidence value that is computed for each image analyzed. The confidence algorithm may take into account information about the local observation angle/IFOV size, probability of clouds, prior information about snow state, etc. The time series of day products are then combined into a multi-sensor/multi-temporal product. The combination of products is done on a pixel-by-pixel basis and controlled by each individual product/pixel's confidence and a decay function of time. The "multi product" should then represent the most likely status of the monitored variable. The sensors applied in this algorithm study are MODIS for optical data and ENVISAT ASAR for SAR data. The study area is South Norway, and the study focuses on the snowmelt seasons in 2003 and 2004.**

Snow cover; multisensor; multitemporal; optical; SAR

I. INTRODUCTION

Snow cover has a substantial impact on the interaction processes between the atmosphere and the surface, thus the knowledge of snow parameters is important for both climatology and weather forecast. The snow cover has also an important impact on water hydrology in regions with seasonal snow. The seasonal snow cover is practically limited to the northern hemisphere. Here, the average snow extent during the winter months ranges from 30 to 40 million km^2. The water equivalent volume of these snow masses ranges from 2000 to 3000 km^3. In the mountainous areas and in the whole North of Europe, snowfall is a substantial part of the overall precipitation, e.g., in Finland 27% of the annual average and in Norway about 50% of the precipitation in mountainous areas is snow.

In order to perform sustainable management of water as one of the most important natural resources for mankind, information of the snow cover is mandatory. The understanding of the relationship between climate and the cryosphere requires the knowledge of the interactions at the snow surface. Snow is also a very sensitive indicator of climate change. In order to further increase the accuracy of weather forecasting models information on the snow coverage and snow properties is of significant importance.

The research institutes NR and NORUT are currently developing algorithms for snow parameter mapping applying a multi-sensor and multi-temporal approach. The focus so far has been on snow cover area (SCA) and snow surface wetness (SSW). Snow wetness is in particular of interest for estimating the time for water runoff from the snow pack. The first results are reported here and include the use of Terra MODIS as the source of optical data and ENVISAT ASAR for Synthetic Aperture Radar data. The overall idea has been to utilize the best features of each sensor for mapping snow in order to increase the ability to monitor the snow more frequently. Optical sensors are able to map the snow cover quite accurately, but are limited by clouds. The SAR penetrates the clouds, but is only able to map wet snow accurately.

II. SNOW COVER AREA ALGORITHM

A. Parameter retrieval algorithms

The optical SCA algorithm is based on an empirical reflectance-to-snow-cover model originally proposed for NOAA AVHRR in [1] and later refined in [2]. The algorithm has recently been tailored to MODIS data by NR. It retrieves the snow-cover fraction for each pixel. The model is calibrated by providing two points of a linear function, corresponding to maximum and minimum reflectance for 0-100% snow cover. The calibration is usually done automatically using calibration areas. Various approaches have been tested for cloud detection and the best results so far have been obtained using a k Nearest Neighbor (kNN) classification approach. The classifier has been trained on a set of partially cloudy images acquired through a melting season.

Several papers have demonstrated the potential of SAR for wet snow detection (like [3,4]) using ERS and Radarsat standard mode. Wet snow was detected by utilizing the high absorption and therefore low backscatter of wet snow pixels and then comparing the backscatter with the corresponding pixel of a reference scene taken during dry-snow or snow-free conditions. Recently, dry snow has also been inferred by using

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digital elevation models (DEM) and the wet snow line to postulate dry snow pixels above the wet snow [5]. The methodology has been further improved by taking into account in-situ air temperature measurements and deriving interpolated temperature fields based on standard 6ºC/km height laps rate. A threshold of –3dB has been used with ENVISAT ASAR Wide Swath imagery to detect wet snow.

B. Overall multisensor algorithm

The overall idea behind the algorithm is to apply daily optical data and supply with SAR data as frequently as practically possible when clouds are present. SAR data will have to be limited to the melting season due to the wet snow requirement. Furthermore, current cost regimes for optical and SAR data will in practice limit the use of SAR data to less than each day. From practical experience so far, approximately two SAR image acquisitions per week seem feasible. The overall algorithm can be written as follows:

$$MSCA_t(x,y) = USCA_i(x,y) \tag{1}$$

for i which gives $max(conf_{MSCA}(USCA_i(x,y))$ $\quad i = t,...,t\text{-}n$

where *MSCA* is the new multi-sensor/time-series SCA product, *USCA* is a time-unit product (a single-sensor product or a day product), $conf_{MSCA}$ is a confidence function for multi-sensor / time-series, t is the current day and n is the number of days in the time series. In other words, for each pixel (x,y) select the "best" day i from a time series of unit products. "Best" means the product with maximum confidence. Hence, the selection process is entirely controlled by the confidence function. The confidence function, $conf_{MSCA}$, is a decay function of time, i.e., a function giving reduced confidence as the age increases of each unit product. The function might be linear giving largest confidence to today's observations and no confidence above a given time horizon. The two main versions of the multi-sensor/time-series algorithm, developed so far and described in the following, differ mainly in their way of producing the time-unit products.

C. NR version

The NR version of the algorithm uses day products for the time-unit products. A day product is defined as a merge of single-image products as follows:

for (each product $SSCA_i$ of this day)
  if ($SSCA_i(x,y)$ = CLOUD) then
    if ($DSCA(x,y)$ = UNCLASS)
      then $DSCA(x,y)$ = CLOUD (2)
  else if ($conf_{DSCA}(SSCA_i(x,y)) > conf_{DSCA}(DSCA(x,y))$)
    then $DSCA(x,y) = SSCA_i(x,y)$

Here, *SSCA* is a single-image product and *DSCA* is the day product (initialized with "UNCLASS"). In other words, if there is a cloud-free pixel in a single-image product for a given pixel position that day select the single-image product pixel with highest confidence. Otherwise, the pixel is set to "CLOUD". The approach assumes that there in general are multiple acquisitions each day, either optical or a mixture of optical and SAR. It is also assumed that the SCA in practice can be regarded unchanged during the day so multiple observations during a day represent observations of the same snow-cover situation.

The day-confidence function, $conf_{DSCA}$, is the product of the single-image confidence function (for either optical or SAR) multiplied by an overall sensor-confidence factor making it possible to give one sensor different confidence from another. The image-confidence function is for optical data typically related to the actual spatial resolution of a given pixel, the likelihood of clouds in a pixel (typically transparent clouds generating mixed pixels) and the assumed snow albedo (which might be quite low late in the melting season).

D. NORUT version

This version of the multi-sensor/time-series algorithm is adapted to a near-real-time approach. Each image used is processed on the fly as they arrive the processing line. In the final step the single-image SCA product is used as input to the multi-sensor/time-series algorithm. The current SCA product and its associated confidence map are used as the basis. The confidence layer gives a SAR-model-based confidence to each pixel in the SCA map based on the classification and the geometry. The new single-image SCA product is subsequently used to upgrade the current multi-sensor/time-series product. The processing line is also able to handle the case when data from different sources arrives at the processing line asynchronously.

III. SNOW WETNESS ALGORITHM

The preliminary results from the work on snow surface wetness are currently limited to time-series analysis, not multi-sensor. The next step is to integrate the two approaches.

A. Optical approach

The ideal approach based on optical would have been to apply a retrieval algorithm for liquid water contents in the snow, like what has been proposed in [6]. However, this would require an imaging spectrometer with optimally located spectral channels for measuring a liquid-water molecular absorption feature. The approach we have used here is to infer wet snow from a combination of measurements of snow temperature (STS) and snow grain size (SGS) in a time series of observations. The temperature observations give a good indication of where wet snow could be present, but are in themselves not accurate enough to provide very strong evidence of wet snow. However, if a rapid increase of the effective grain size is observed simultaneously with a snow surface temperature of approximately 0°C, then this is a strong indication of a wet snow surface. A simplified version of the algorithm used is expressed below (Pixel indexing has been skipped for clarity.):

if *SGS*(today) - *SGS*(recently) > SGStresh AND
  -2 < *STS*(today) < 1 then *MSSW* = WET_SNOW
else (3)
if *SGS*(today) < BareGroundSGStresh then
  MSSW = BARE_GROUND
else
if *STS*(today) > 1) then
  MSSW = BARE_GROUND

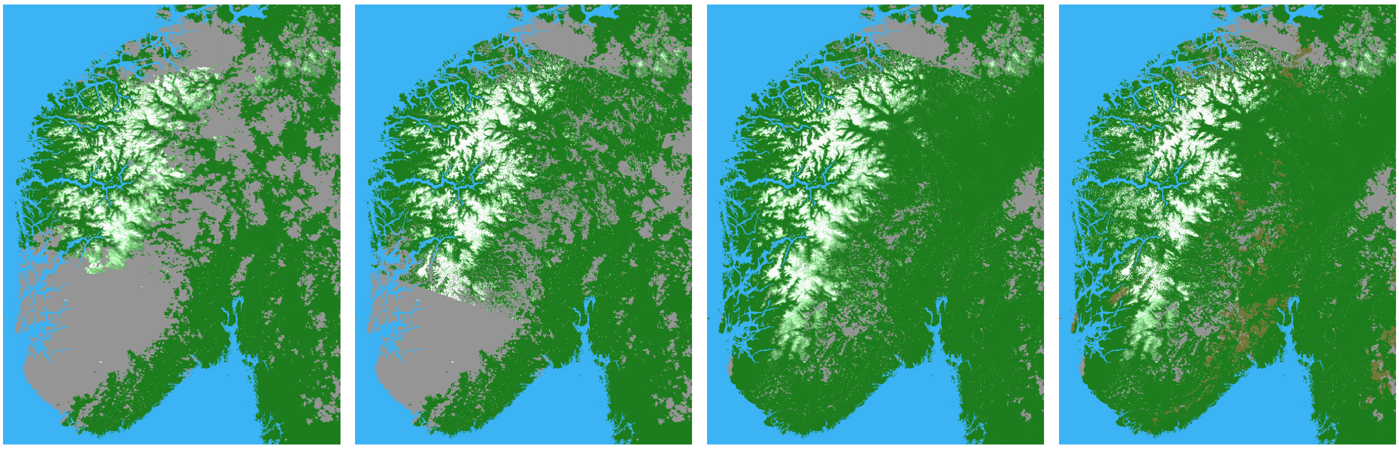

Figure 1. Multi-sensor/time-series snow cover maps from the period 9-12 May produced by the NR version of the algorithm. Fractional snow cover is shown on a scale from green (bare ground), via tones of green to white (100% snow cover). Clouds are shown in grey

else
$MSSW$ = DRY_SNOW

The algorithm also illustrates how bare ground is inferred from temperature observations above 0°C and a rapid developing negative gradient for SGS (both due to appearance of bare ground patches at the sub-pixel level).

The STS algorithm is based on Key's algorithm [7,8], which we in a pilot study identified as one of the best single-view techniques for retrieval of STS for polar atmospheres, and it can be applied on MODIS as well as AVHRR data. For SGS we used a normalized grain size index based on work in [9] and followed by experiments in [10]. MODIS channels 2 and 7 have been used because the index then has been shown to be less sensitive to snow impurities.

B. *SAR approach*

Radar frequencies are extremely sensitive to snow wetness. The observed backscattering from snow is a sum of contributions from the air-snow interface, the snow volume and the snow-soil interface. The backscattering is a complicated function of surface parameters (roughness, correlation length, and wetness), snow parameters (density, depth, grain size, and water content) and soil parameters (surface roughness and moisture) in addition to sensor parameters (frequency, polarization, and incidence angle). If the snow is wet, the dominating contribution comes from the snow surface, due to absorption. In [11] algorithms were demonstrated for retrieval of snow wetness from multi-polarization SAR. For single polarization SAR (such as ENVISAT ASAR Wide Swath) there is too many parameters involved in the equation to facilitate a full inversion of the problem. Several authors have, however, shown that wet snow can be detected (see [3]).

In Figure 4 we demonstrate that SAR can be used as a sensitive instrument to detect the presence of a wet snow surface. We have scaled the difference in backscatter cross-section between dry and wet snow condition to a 0-15% scale and corrected for incidence angle, to produce a wet snow product. More advanced and future algorithms will aim at inverting the full multi-parameter problem by, e.g., suitable simplified backscatter models.

IV. Experimental Results

A. *Snow cover area*

a) *NR version*

The NR version of the SCA multi-sensor/time-series algorithm has been tested for the time period of May 9-31, 2004 when the snowmelt was ongoing in South Norway. For each day there was at least one MODIS image. An optical day product was produced for each day, except for the days when the calibration areas has been masked out by the cloud mask (11-14, 17 May). The time series included 5 ASAR images: 9, 12, 19, 25, 31 May 2004.

The time series analysis were tested with different setting for the use of ASAR products:

- Without ASAR product,
- Using ASAR SCA with dry and wet snow,
- Using ASAR with wet snow only,
- Using ASAR wet snow with reduced confidence.

We found that the use of ASAR SCA did improve the time-series product, that using only wet snow appears better than including assumptions about dry snow in the ASAR product, and that the confidence of ASAR should be set lower than for cloud free MODIS data from the same day.

We present results from the test run where the ASAR confidence was set to 50% of its original value, and only wet snow observations were taken into account. Four samples of the produced maps are shown in Figure 1.

Day product 9 May: The results from the first day in the test period are shown in the left and the second left map. These day products are equivalent to a situation with time-series products after a period with cloud coverage. The left map shows the optical result only, and the following shows the product after the ASAR product has been included. In this situation the ASAR image covers the cloud free areas and a

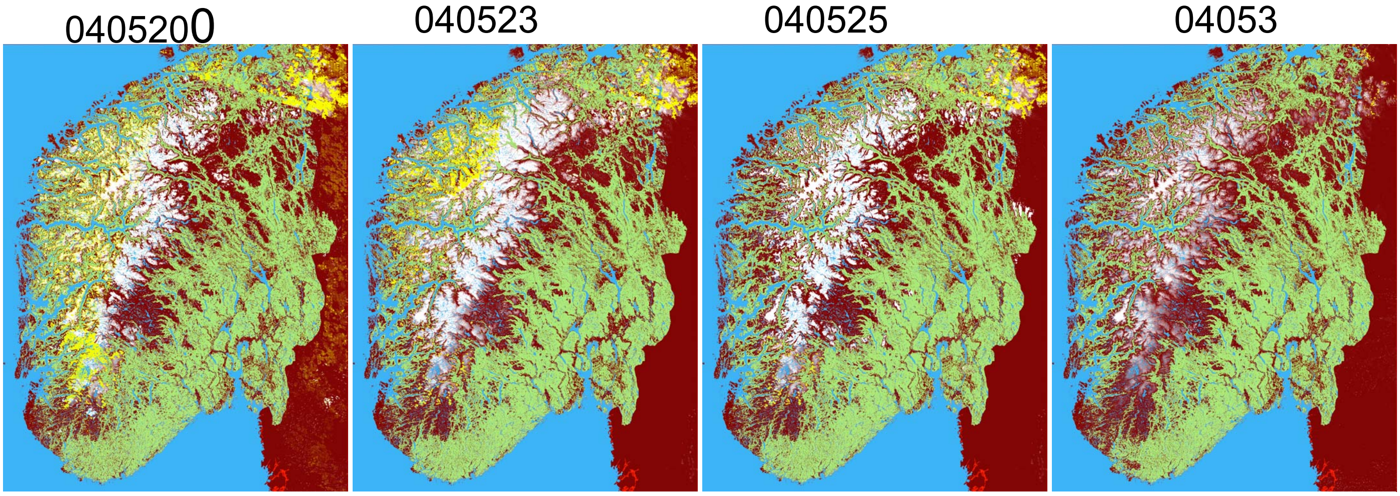

Figure 2. Examples of multi-sensor/time-series SCA products over Southern Norway for a period of 11 days in May 2004 produced with the NORUT version of the algorithm. Yellow denotes clouds, and is most prominent in the beginning of the period

little bit more, and we see that the results seem to agree. The SCA from the ASAR image has in general a bit lower values that the optical SCA product.

Time-series product 10 May (third from left): The area covered by data has increased and we see almost the whole South Norway. Where SCA from ASAR has been replaced by the newest observations, the values have increased and are in correspondence with the optical day product from the previous day.

Time-series product 12 May (map to the right): Due to clouds there are no optical product this day or the day before. The existing observation from above has now been reduced its confidence and partly been replaced by the current ASAR product. In the western part we see that reduced SCA values have been introduced by the ASAR observations. In the east we see that the confidence has decayed below a threshold (indicated by brown color). The reason why it has not been updated is that the ASAR product has zero confidence (near the image center) or is outside the frame (below the image center). This illustrates that the current approach ASAR is not capable to verify snow-free areas.

b) NORUT version

Figure 2 shows an example of multi-sensor/time-series SCA product based on the NORUT version of the algorithm. In addition to the SCA product an image indicating the source is also shown. The multi-sensor/time-series confidence map is also shown. For demonstration, a near real time multi-sensor/time-series for the period April 20 - June 31, 2004 has been produced. Each time a new single-image product was made a multi-sensor/time-series product was also produced. A decay function cut-off has currently been set at one week old contributions to the SCA product. In Figure 2 image samples from the period May 20-31 is displayed. Areas without SAR coverage is clearly more clouded than areas with SAR coverage. When studying the details of the imagery it is also evident that the pixels with SAR contribution have a higher contrast (either 0% or 100% SCA) than optical images.

B. Snow surface wetness

a) Optical version

The optical SSW algorithm has been tested on a time series of MODIS images from April 2003. For each day in the period STS and SGS have been calculated from MODIS L1B data with pixel size 1 km. The inference of SSW for a certain date has been done using the STS and SGS for the current day and the SGS from one to a few days before.

The series of products starts at 14 April. At that time there was a cold period in South Norway. In the mountain areas, the temperature around 1000 m above sea level had been below zero for some days, and in the higher areas even lower. A period of warm and sunny weather starts 15 April. The temperature rises also in the mountain areas and reaches as high as +10°C at 1000 m around 18-20 April.

For the two classes in the range $-2°C < STS < +0.5°C$ the change in grain size is given by: Decreasing SGS: dark blue, dark orange (hardly no examples); Almost constant grain size, change in grain size index less than 2 units: medium blue and orange; and increase in grain size: light blue and yellow. Clouds are shown in gray. Some comments to the products are given in the following.

Product 14 April (period 8-14 April): The product is made from the images of 14 and 8 April. The map shows mostly cold dry snow, which is probably correct. Only in the lower areas in the south the snow temperature has come close to zero.

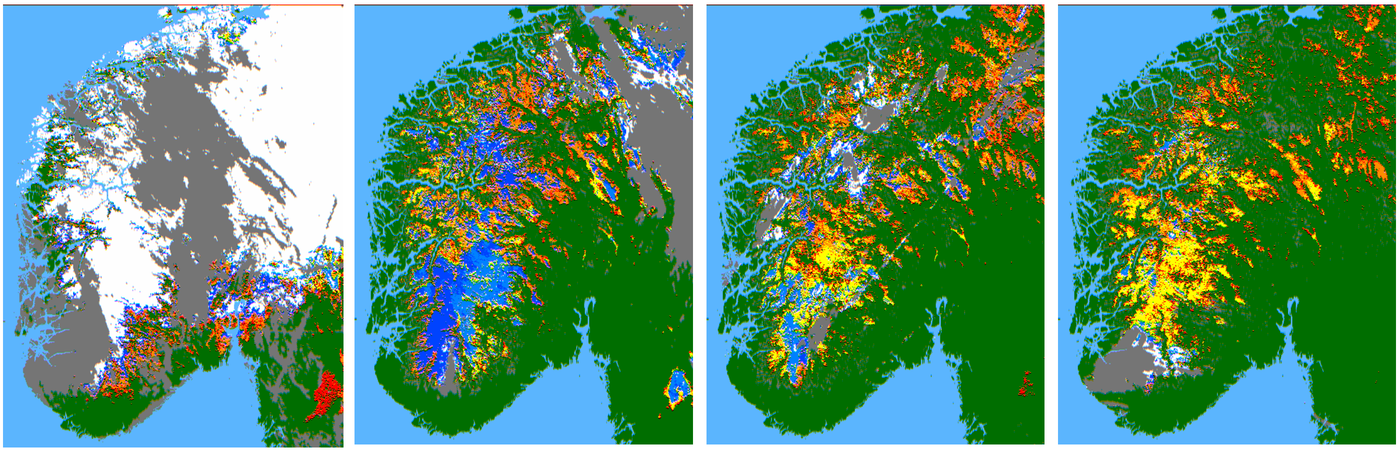

Figure 3. Four samples of the snow-wetness product from the NR version of the SSW algorithm from the period 14-20 May 2003. The colors indicate the following classes: STS < -2°C, dry snow (white); -2°C < STS < -0.5°C, on the edge of becoming moist (blue); -0.5°C < STS < +0.5°C, moist (orange/yellow); +0.5°C < STS < +1°C, wet (red), and STS > +1°C: partly or completely bare ground (green)

Product 16 April (period 14-16 April): This map shows a completely different situation. There are hardly any areas with cold snow left. In the highest areas the snow temperature still lies below zero (blue), but in the lower parts the snow is probably starting to become wet. Note the lighter blue and yellow colors in the south/east mountain area compared to south/west, which is probably due to warmer wind east of the watershed.

Product 18 April (period 16-18 April): Still some snow with temperatures below zero, but most of the snow has come close to zero degrees. The yellow color signifies that the grain sizes have increased since the 16th. Evidently, some clouds misclassified as snow.

Product 20 April (period 16-20 April): Compared to the 18th, more areas have reached zero degrees and the areas of isolated snow are shrinking. Especially in the north some areas seem to have vanished. The snow has probably not vanished completely, but the pixels contain a mixture of snow and bare ground, and this influences the calculated temperature.

b) SAR version

The SAR SSW algorithm has been run continuously in parallel with the SAR SCA algorithm, and has produced 16 SSW products. The time series has been studied and shows consistent time behavior. An example of a sub-section of a SSW map is shown in Figure 4. Comparisons with in-situ measurements from the 2004 field season are planned.

V. DISCUSSION AND CONCLUSIONS

A. Snow cover area

The first experience with the NR version of the multi-sensor/time-series algorithm shows that the results depend very much on how the initial single-image product confidence is set and on the time decay function. It appears that closeness to clouds should give reduced confidence in optical data in order to reduce the risk of classifying clouds as snow. More

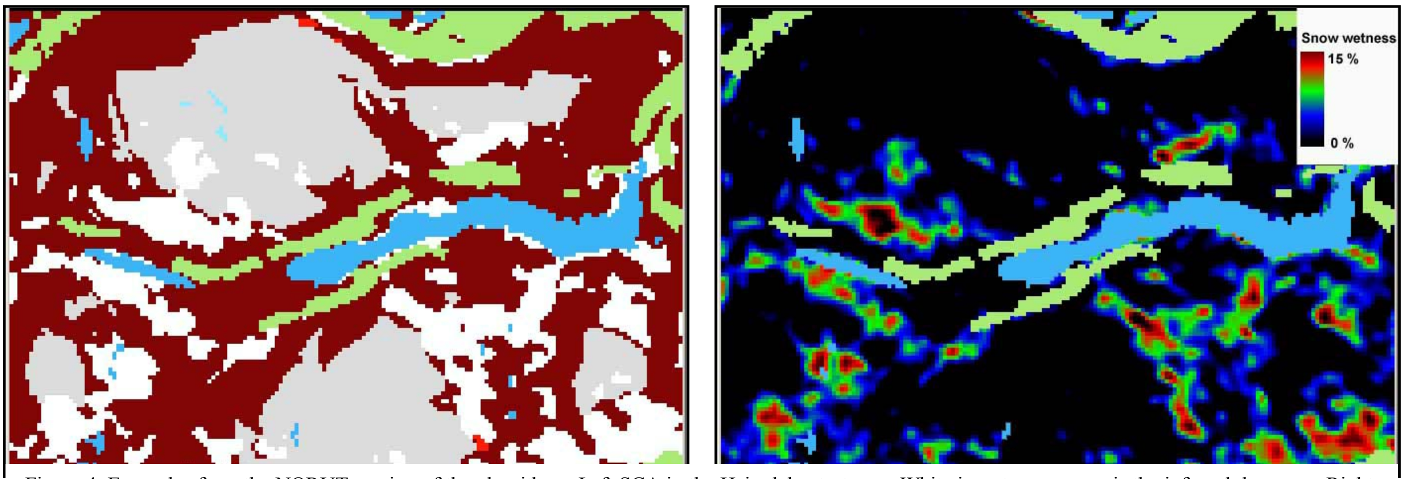

Figure 4. Examples from the NORUT version of the algorithms. Left SCA in the Heimdalen test area. White is wet snow, grey is the inferred dry snow. Right: Scaled differential backscattering from wet snow for the same image. The areas with wet snow have high differential backscattering between the reference dry snow scene and the current wet snow. As a first order approximation this difference is set proportional to the snow wetness

important, however, is to consider how to fuse the SAR and optical products better. The algorithm would probably give enhanced results if wet snow and dry snow from the SAR product had been handled differently, in particular when the pixels consists of a mixture of wet and dry snow or bare ground.

The experience with the NORUT version confirms that interpretation of SCA from SAR imagery is not as straightforward as for optical imagery. In the original 100 m SAR product the wet snow threshold is binary (wet snow/non-wet snow). Due to the logarithmic coding of backscatter in SAR imagery a small fraction of bare soil in a SAR pixel may cancel out a large fraction of snow. Also, the resampling of 100 m products to 250 m generates a fractional snow coverage where bare soil, wet and dry snow and maybe also mask pixels are combined into a snow-cover fraction. There is a need to harmonize the fusion of SAR and optical SCA retrieval in the future.

The results of the study showed that SAR-based maps in general were consistent with optical-based maps. The SAR-based maps were very useful for updating the multi-sensor/time-series products in a period of missing optical observations. The SAR products were confirmed by subsequent optical SCA observations. However, for some places the SAR wet SCA values had a tendency to underestimate the SCA, compared to optical data. When dry snow estimates were included in the radar products, the tendency was the opposite.

B. Snow surface wetness

The optical experiments done so far have confirmed that the approach of combining STS and SGS analyzed in a time series of observations can be used to infer wet snow, including giving an early warning of snowmelt start. Air temperature measurements from meteorological stations confirm the maps produced in general. The main problems observed so far in the products produced are related to clouds. In some maps it is observed that dry and cold snow is more frequent close to clouds. One could imagine that this is because the clouds have kept the sunlight away – hence the snow has not been warmed. But it might as well be that parts of the clouds have not been detected in the MODIS cloud product, which so far has been used in the experiments (the kNN cloud product will be used in the future). The problems are typically associated to transparent clouds.

The SAR experiments have confirmed that SAR can be used to detect the presence of wet snow. The generation of qualitative correct snow surface products is in development. There is a need to invert simplified backscatter models to obtain approximate correct results for the liquid water content in the snow surface.

Comparisons between SSW products derived from SAR and optical sensors have not yet been carried out thoroughly. More detailed comparisons as well as validation work will be carried out in the near future. A multi-sensor version for the SSW products is also under development. The common framework applied for multi-sensor/time-series SCA will also be used for SSW.

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REFERENCES

[1] T. Andersen, "Operational snow mapping by satellites," Hydrological aspects of alpine and high mountain areas, Proceedings of the Exeter symposium, July 1982, IAHS publ. no. 138, pp. 149-154.

[2] R. Solberg and T. Andersen, "An automatic system for operational snow-cover monitoring in the Norwegian mountain regions," IGARSS 1994, Pasadena, California, USA, 1994.

[3] T. Nagler and H. Rott, "Retrieval of wet snow by means of multitemporal SAR data", IEEE Trans. Geoscience and Remote Sensing, Vol. 38, No. 2, March 2000, pp. 754-765.

[4] J. Koskinen, S. Metsämäki, J. Grandell, S. Jänne, L. Matikainen, M. Hallikainen, "Snow monitoring using radar and optical satellite data," Remote Sensing of Environment, vol. 69, no. 1, pp. 16-29, 1999.

[5] E. Malnes and T. Guneriussen, "Mapping of snow covered area with Radarsat in Norway," Geoscience and Remote Sensing Symposium, (IGARSS), 24-28 June 2002, Vol. 1.

[6] R.O. Green and J. Dozier, "Measurement of the spectral absorption of liquid water in melting snow with an imaging spectrometer," Summaries of the Fifth Annual JPL Airborne Earth Science Workshop, January 23-26, 1995, JPL Publication 95-1, pp. 91-94.

[7] J. R. Key, J. B. Collins, C. Fowler, and R. S. Stone, "High-latitude surface temperature estimates from thermal satellite data," Remote Sensing of Environment, 1997. 61(2): p. 302-309.

[8] J.R, Key, "Polar surface temperature retrieval from space: coefficients", http://stratus.ssec.wisc.edu/products/surftemp/surftemp.html., 2003.

[9] J. Dozier, "Spectral signature of alpine snow cover from the Landsat Thematic Mapper," Remote Sensing of Environment, vol. 28, pp. 9-22, 1989.

[10] Fily, M. Bourdelles, B. Dedieu, J.P. Sergent, C, "Comparison of In Situ and Landsat Thematic Mapper Derived Snow Grain Characteristics in the Alps," Remote Sensing of Environment, Vol. 59, No. 3, p. 452-460.

[11] J. Shi and J. Dozier, "Infering snow wetness using C-band data from SIR-C polarimetric SAR," IEEE Trans. Geosci & Remote Sens., 33, pp. 905-914, 1995.