Improving runoff modelling using satellite-derived snow covered area?

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Abstract Operational use of satellite-observed snow covered area (SCA) in the HBV model was studied in order to improve the spring flood prediction. The study included calibration of HBV models against both discharge and SCA, against discharge only, and updating of the HBV models based on satellite observed SCA. Ten test catchments were selected for the study. The results confirmed that HBV models calibrated against SCA in addition to discharge simulate discharge nearly as well as models calibrated against discharge only. The simulated SCA was markedly improved when SCA was included in the calibration.

Deviations between observed and simulated SCA was used to trigger model updates. In such cases, the model input (precipitation and temperature) was adjusted until a reasonable fit in the SCA was obtained. The results of the updates were ambiguous. Only 28% of the updates improved the runoff simulations. Improved simulations were most frequent at large SCA values.

SCA derived from radar and optical satellite sensors differed considerably. Harmonisation is required before both types of data can be integrated in the same model simulations.

Keywords Hydrology; remote sensing; runoff; satellite; snow

Introduction

Background

Information about snow amounts is important for flood warning and planning of energy production in Norway. Snowmelt contributes significantly to most severe flooding situations in larger rivers, as in south-eastern Norway in 1995. Refilling of the hydropower reservoirs after the winter season is also dependent on the amount of snow. During winter and spring 2002–03 the water levels in the reservoirs was extremely low and updated snow information was crucial for the authorities in order to decide on eventual restrictions in the electricity production. The Norwegian Water Resources and Energy Directorate (NVE) is responsible for the management of Norway's water and energy resources and for the national flood warnings. NVE uses "The Nordic HBV model" (Sælthun 1996) to simulate runoff in the river systems and the inflow to the hydropower reservoirs. Satellite-derived snow covered area (SCA) is used for comparisons to the simulated SCA by the HBV model. Operational updating of the HBV model, based on satellite-derived SCA, is applied only to the test catchments in this study.

Two models much used in operational runoff forecasting, for areas with considerable snowmelt flood contribution, are the SRM model (Martinec *et al.* 1998) and the HBV model. Using the SRM model, Martinec and Rango (1987) demonstrated that satellite-derived snow cover data could be useful in hydrological modelling. This model is designed for remotely sensed SCA input and is used in several countries (Martinec *et al.* 1998), e.g. USA, Spain and

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Austria (Owe *et al.* 2001; Gómez-Landesa and Rango 2002; Rango *et al.* 2003; Nagler *et al.* 2004), especially for short-range forecasts during snowmelt. The HBV model is primarily used in the Nordic countries for operational forecasts in a large number of catchments. The model simulates the snow water equivalent (SWE) in addition to SCA and the model is thus able to forecast the total spring flood volume for catchments with accumulated winter snow. The model requires no satellite data as input, and it is also designed for catchments or times of the year without snow. Previous work in the projects Snowtools (Guneriussen *et al.* 2000) and Hydalp (Rott *et al.* 2000) showed that updating the HBV model with remotely sensed SCA data tended to reduce the model performance. The main reason for this could be that SCA data was not used in the model calibrations. Further work by Johansson *et al.* (2003), Metsämäki *et al.* (2003), Huttunen *et al.* (2005) and Engeset *et al.* (2003) have shown that the HBV model is able to simulate SCA on a catchment scale in accordance with observed SCA, without losing precision in the runoff simulations, when SCA is included in the calibrations. Engeset *et al.* (2003) showed that observed meteorological model input could be unsatisfactorily correlated to the actual meteorological situation in the model catchments in years with abnormal weather conditions. In such years an update of the input data, in order to simulate SCA properly before the main flooding period, could improve the runoff simulations.

However, the results from the different studies are divergent when it comes to operational use of satellite data. Ongoing work in Germany (Schulz *et al.* 2003) aims to improve operational runoff forecasts by assimilation of satellite data in a distributed hydrological model called LARSIM (Bremicker 2000).

Objectives

The objective of this study was to investigate where and when inclusion of satellite-derived SCA could improve runoff simulations, especially in flood warning and energy production planning. An important issue has also been to investigate if SCA derived from different sources could be used for model updating. This work builds on the results and methods from Engeset *et al.* (2003) where three test catchments were investigated. However, in this work we have studied seven additional catchments. The catchments are selected from different parts of the country and span over a larger range of field characteristics, i.e. catchment size, altitude level and topography, than those used in Engeset *et al.* (2003). In order to extend the data set used in the analysis, two additional years of data are included. Furthermore, this study uses time series from other satellite sensors. In addition to the NOAA AVHRR data optical data from Terra MODIS and radar data from Envisat ASAR are used. For the ASAR data a new algorithm for classifying dry snow has been tested.

Study area and data sets

Study catchments and hydro-meteorological data

Ten catchments were selected for the study. Eight of the catchments are located in mountain areas in southern Norway and two of the catchments are located in northern Norway (Figure 1 and Table 1). The catchments represent different altitude ranges, area sizes and geographical locations. They were chosen in order to run models operationally, and to cover essential rivers in Norway. For all catchments the snow melt flood in spring and summer is usually the dominating flood each year. To ensure reliable SCA estimates from the satellite images, mainly non-forested or sparsely forested areas were used in the studies. One or two meteorological stations in each catchment provided daily observations of air temperature and precipitation. A runoff gauge, at the outlet of each catchment, provided daily discharge values. Data for the period 1 September 1994 to 1 September 2004 was used. A broader presentation of the data and simulations used in this study is given in a report by Alfnes and Udnæs (2004).

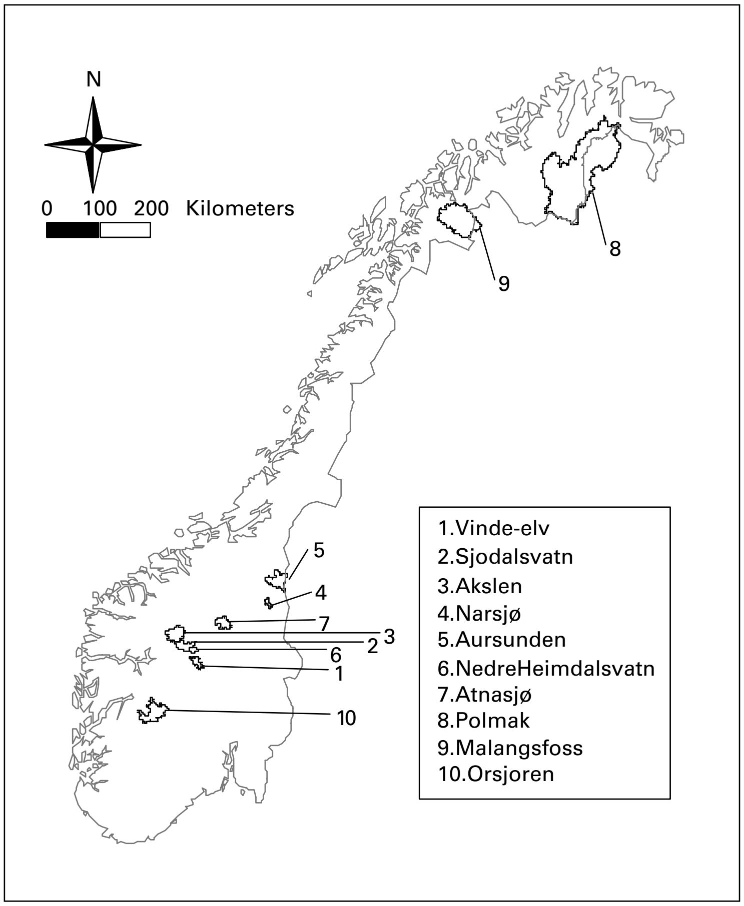

Figure 1 Location of the ten catchments used in the study

Satellite data

Satellite data was retrieved from two optical sensors, NOAA AVHRR and TERRA MODIS, and one radar sensor, Envisat ASAR. The spatial resolution of the SCA products was 1 km for the AVHRR data and 250 m for the MODIS and ASAR data. Time series of SCA were derived from AVHRR imagery for the period 1995–2004 and used for calibrating and validating the HBV model. Between 30 and 40 SCA maps were derived for each of the two catchments in northern Norway, whereas 60 to 90 SCA maps were derived for each of the eight catchments in southern Norway. MODIS and ASAR data from 2004, covering the eight catchments in southern Norway, was compared to the AVHRR data in order to evaluate if these data could be used for updating the models in addition to the AVHRR data. Between 4 and 8 SCA maps were made for each catchment and sensor based on the MODIS and ASAR data.

Methods

Hydrological modelling

"The Nordic HBV model" is a modified version of the HBV model (Bergström 1992). The model structure is a sequence of four submodels for snow, soil moisture, dynamics and routing. The model is divided into ten elevation intervals. Observed precipitation and temperature are model inputs. The main output from the simulations is runoff, but SWE and SCA for each elevation interval are also calculated. After snow accumulation the model always simulates 100% SCA, and simulated SCA is not reduced until the first occurrence of

Table 1 Description of the ten test catchments used in the HBV simulations. The alpine areas are defined as areas above the tree-line

Catchment	No. in map (Figure 1)	Annual runoff (mm)	Area (km^2)	Altitude median–max–min (m a.s.l.)			Alpine (%)	Forest (%)
Vinde-elv	1	487	268	985	1686	560	59	41
Sjodalsvatn	2	1257	474	1465	2400	940	100	0
Akslen	3	966	791	1476	2472	480	84	16
Narsjø	4	575	119	934	1595	737	66	34
Aursunden*	5	764	835	840	1553	690	59	41
Nedre Heimdalsvatn*	6	875	130	1303	1843	1053	96	4
Atnasjø	7	671	465	1186	2114	701	78	22
Polmak	8	384	14165	355	1067	20	51	49
Malangsfoss	9	847	3118	719	1677	20	70	30
Orsjoren	10	840	1192	1231	1531	951	98	2

*Catchment where runoff is represented by calculated reservoir inflow

melting. For each elevation zone the accumulated snow is distributed according to a log-normal probability density function. The snow melt intensity is uniformly distributed over the snow covered area. The shape of the log-normal distribution is determined by the coefficient of variation, *CV*. Hence the value of *CV*, which is calibrated within reasonable limits, controls the relationship between SWE and SCA during the melt period.

The HBV model was automatically calibrated for the ten catchments using the parameter estimating routine PEST (Brebber *et al.* 1994), which is a local gradient based search procedure. Global optimization methods (e.g. Duan *et al.* 1992; Madsen 2000) might have given more confident optimal parameter sets. However, due to a relatively short calibration period, the confidence of one optimal parameter set would still be limited for a longer period. Data from the period 1 September 1995 to 31 August 1999 was used for calibration. The model was calibrated in two modes for each catchment: (1) against runoff only, and (2) against both runoff and SCA. To avoid unintended bad calibrations, 96 model calibrations, with different initial parameter values, were run for each catchment and for each mode. Due to the short calibration period, the best five parameter sets out of the 96 calibrations were chosen for further comparisons in the validation period. Out of the five best parameter sets possible unacceptable parameter sets could be detected in the validation period.

Since the models were calibrated on different data types, the data was weighted in the calibrations. The PEST routine searches a local minimum by optimizing the objective function

$$\phi = \sum_{i=1}^{n} \left[w_i (X_{obs,i} - X_{sim,i}) \right]^2 \qquad (1)$$

where $X_{obs,i}$ is the observed value at time i, $X_{sim,i}$ is the simulated value, w_i is a weighting factor and n is the number of observations. When several types of observations or objectives are included in the calibration an aggregate objective function

$$\phi_{tot} = \phi_1 + \phi_2 + \cdots + \phi_p \qquad (2)$$

is optimized. Madsen (2000) proposed to use an aggregated objective function that puts equal weight on the different objectives. In this study, the objectives were daily runoff (Q), snow covered area (SCA) and, in order to maintain the water balance in the model, accumulated runoff (Q_{tot}). The weighting factors of Q were set to 0 during the first month, thereafter equal to 1. The typical ϕ_Q obtained for the best models were thereafter used to calculate the weighting factors for SCA and Q_{tot} by setting

$$w_{SCA,i} = \sqrt{\phi_Q}/\sqrt{nE_{SCA}} \tag{3}$$

where E_{SCA} is the maximum accepted error in the simulated SCA, and similar for Q_{tot}. We used $E_{SCA} = 5$ and $E_{Q\mathrm{tot}} = 5$ percentage of $Q_{\mathrm{tot,obs}}$. Using this approach the different objectives were given equal weight in the aggregated objective function.

Validation of the models was performed on the periods 1 September 1994–31 August 1995 and 1 September 1999–31 August 2004. These periods were also used to investigate whether updating the model based on SCA observations would improve the simulations. The best parameter set from the validation was used in this investigation. An update was triggered by either (a) a deviation between observed and simulated SCA greater than 20% units at a single satellite scene or (b) three succeeding deviations of at least 10% units within ten days. In such cases the model input was updated by a percentage change of the winter precipitation and/or temperature modifications immediately ahead of and during the melt season until the date of the triggering observation. In this study the updating was done manually by gradually increasing or decreasing the precipitation and/or temperature until acceptable SCA (within 10% deviation from the observed ones) were achieved. NVE has recently developed automatic update procedures for operative use of SCA from satellite data. In these procedures the simulated snow pack is directly updated. Comparisons between the automatic procedure and the method used in this work showed no obvious differences with respect to runoff simulations (Alfnes *et al.* 2005).

SCA retrieval

Two methods were used to retrieve SCA from AVHRR, a method described by Schjødt-Osmo and Engeset (1997) and the Norwegian-Linear-Reflectance (NLR) method described by Solberg and Andersen (1994). Both methods are based on converting band 2 pixel values into SCA using a linear transformation and deriving SCA at the subpixel level. The transformation is calibrated for each image using snow on glaciers for 100% SCA and snow-free land as 0%. The MODIS data was also handled with the NLR method. SCA was derived from ASAR data using the Nagler algorithm (Nagler and Rott 2000; Malnes and Guneriussen 2002) for detecting wet snow. The algorithm was refined using temperature data (Malnes *et al.* 2004) to avoid misclassifications between dry snow and bare ground.

In most of the test catchments observed SCA rarely exceeds 75% on a catchment scale, mainly due to vegetation and shadow effects. Hence the satellite-based SCA was transformed linearly to harmonize with the HBV simulations, covering the entire interval from 100% to 0% SCA during the melting season, before use in model calibrations. This transformation may lead to SCA values above 100%, especially when the snow is fresh with high surface reflectance. In such situations the SCA was set to 100%. Because of impurities in the snow surface and differences in the surface reflectance between the test catchments and the training areas defining the 100% SCA reflectance, expected errors in SCA could be as large as 40% in the late melting season (Rune Solberg, personal communication).

In real-time forecasting the satellite data is normally included in the hydrological modelling the day after acquisition. The optical data are not used if more than 30% of the catchment is covered by clouds. The SCA data is also combined with a digital elevation model to reveal possible misclassifications or improper geometrical correction uncovered by abnormal relationships between elevation and SCA. Forecasted temperature and precipitation for each catchment are used as input to the models simulating runoff and SCA for a six day forecast period.

Results and discussion

Model calibration and simulation

Calibration against SCA in addition to runoff improved the simulated SCA considerably (Figure 2 and Table 2). While the Nash and Sutcliffe (1970) criterion on SCA, R^2_{SCA}, ranged from 0.45 to 0.98 (median $=$ 0.86) for the best Q models (models calibrated against runoff only), R^2_{SCA} ranged from 0.90 to 0.99 (median $=$ 0.94) for the best QS models (models calibrated against runoff and SCA). The effect on the simulated runoff, measured by R^2_Q, was slightly negative when SCA was included. R^2_Q ranged from 0.76 to 0.94 (median $=$ 0.85) for the Q models and from 0.73 to 0.94 (median $=$ 0.83) for the QS models.

The model runs were validated by simulating runoff and SCA over test periods from 1 September 1994 to 31 August 1995 and from 1 September 1999 to 31 August 2004. Simulations for the test periods were validated against observed runoff and SCA. The results showed that the QS models were of the same quality as the Q models with respect to runoff, yielding a general poorer result than in the calibration period. The model performance with respect to SCA also decreased, especially for the QS models. This indicates a potential for improvement of the model results through the updating procedure. The observed decrease in performance may also be a result of the quality variations in the SCA product. For two of the catchments, Orsjoren and Nedre Heimdalsvatn, the terrain is relative flat and non-forested. The reduced model performance regarding SCA was minor in the validation period compared to the calibration period for these catchments. This result indicates that the quality of the SCA product is less variable for such areas. A detailed description of the calibrations and simulations are given in Alfnes and Udnæs (2004) and Alfnes *et al.* (2005).

Model updating

Positive trigger responses, defined as deviation between simulated and observed SCA, were found in 40 cases (each case represents one model year). Nineteen of these were subjectively rejected from updating since the observed SCA values were assumed unlikely when compared to the stage of melting in the catchment. Thus, updating scenarios were calculated in 21 cases.

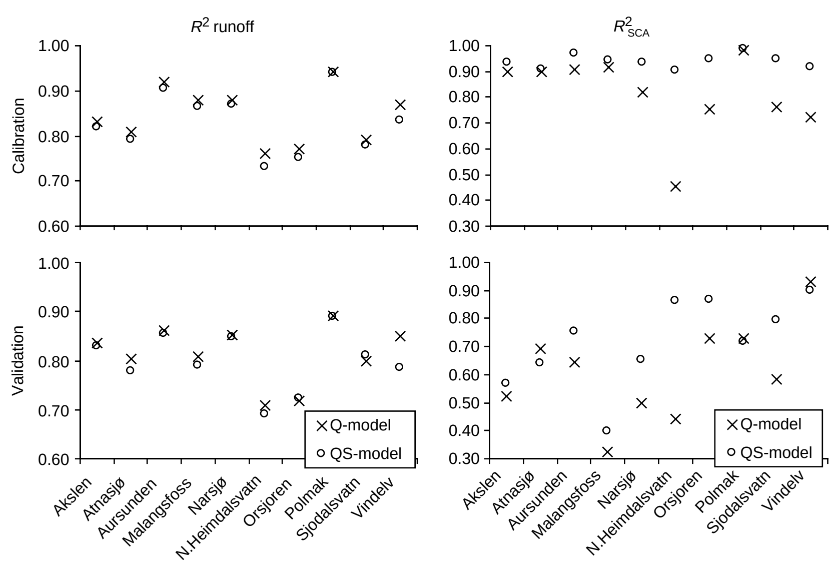

Figure 2 Model performance, based on the Nash–Sutcliffe coefficient R^2, using the Q and the QS models respectively in the calibration and validation period. The Q models are calibrated against runoff while the QS models are calibrated against runoff and SCA

Table 2 Model performance of the five best models from the automatic calibration. The table shows the mean R^2 value of the five best models for the discharge (Q) and the snow covered area (SCA) in the calibration (calib.) and validation (valid.) period and when updating model input (update) in the validation period. The overall results of the model update are indicated with the $+/-$ signs

	Q models				Q + SCA models					
	R^2_Q		R^2_{SCA}		R^2_Q			R^2_{SCA}		
Catchment	**calib.**	**valid.**	**calib.**	**valid.**	**calib.**	**valid.**	**update**	**calib.**	**valid.**	**update**
Akselen	0.83	0.84	0.90	0.52	0.82	0.83	0.84 +	0.93	0.57	0.87
Atnasjø	0.81	0.80	0.90	0.69	0.79	0.78	0.74 −	0.91	0.64	0.77
Aursunden	0.92	0.86	0.91	0.64	0.90	0.85	0.80 −	0.97	0.75	0.86
Malangsfoss	0.88	0.81	0.92	0.32	0.86	0.79	0.73 −	0.94	0.40	0.67
Narsjø	0.88	0.85	0.82	0.50	0.87	0.85	0.86 +	0.94	0.65	0.68
N.Heimdalsvatn	0.76	0.71	0.45	0.44	0.73	0.69	0.66 −	0.90	0.86	0.88
Orsjoren	0.77	0.72	0.75	0.73	0.75	0.72	0.77 +	0.95	0.87	0.91
Polmak	0.94	0.89	0.98	0.73	0.94	0.89	0.89	0.99	0.72	0.89
Sjodalsvatn	0.79	0.80	0.76	0.58	0.78	0.81	0.83 +	0.95	0.79	0.89
Vinde-elv	0.87	0.85	0.72	0.93	0.83	0.79	0.83 +	0.92	0.90	0.95

The model update revealed diverging results. Two examples are shown in Figure 3. In the Akslen catchment the simulated SCA was far below the observed during snow melt in 2001 (Figure 3(a)). By increasing the winter precipitation and decreasing the spring temperature the maximum level of the flood was drastically improved although the first flood peak was overestimated. In the Narsjø catchment the observed SCA was far below the simulated one at the beginning of the spring flood in 2002 (Figure 3(b)). However, the runoff was well simulated and the observed SCA was subjectively considered to be underestimated. This year

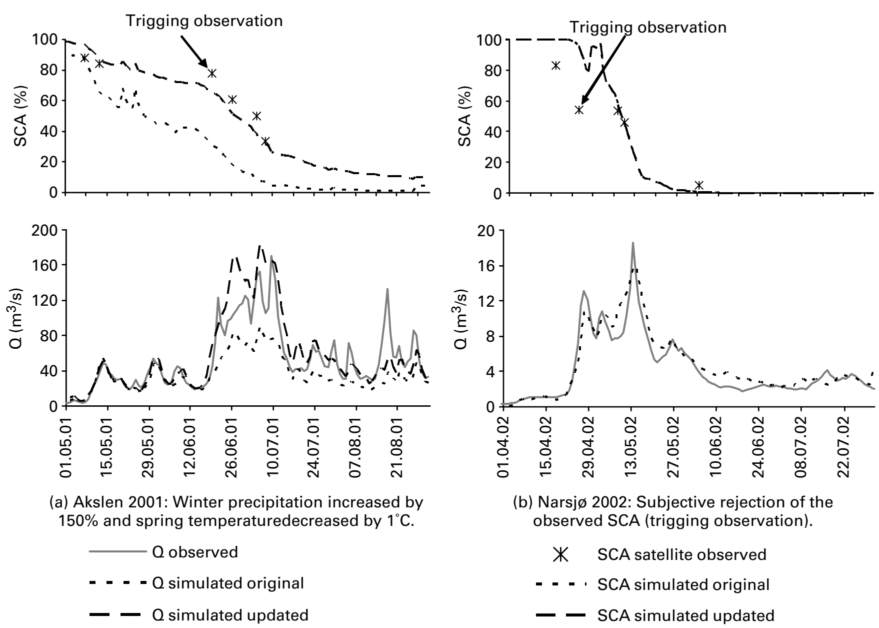

Figure 3 Example of model runs with and without updated winter precipitation and spring temperature. (a) Simulated runoff during the spring flood was increased to a level similar to the observed one. (b) Subjective rejection of the observed SCA. Reduction of winter precipitation in order to simulate SCA in accordance to the observed SCA would have led to a drastic underestimation of the flood volume

the snowmelt started earlier than normal in the Narsjø catchment and the reflectance was probably much lower than in the training areas used for estimating 100% SCA.

Eleven cases, mainly in 2001 and 2003, showed improvement in the amplitude of the flood peaks and the accumulated discharge volumes, whereas the model performance was worsened or unchanged in the remaining cases. An overall improvement in model performance with respect to runoff was seen in five of the ten test catchments (Table 2 and Figure 4). The R^2_{SCA} was, naturally, increased for all models. The successes in 2001 can be explained by abnormal weather conditions. The prominent snow-producing weather circulation came from the south-east as opposed to from the west, which is normal. Thus, the observed precipitation was not representative for several of the test catchments. This was detected and corrected using the satellite-observed SCA. In 2003 several successful updates were achieved. In this year the snow melt started one to two weeks earlier than normal in the test catchments. Early snowmelt was also the case in 2004. However, no successful updates were obtained for this year. Thus, early snowmelt alone cannot explain the positive response in 2003.

No obvious explanation of when and where the updates are successful has been found. The successes and failures seem to be randomly spread between catchments at different altitude and geographical location. A tendency of higher success rate at large observed SCA values was found, although to weak to draw any conclusions. A reasonable explanation is that the snow reflectance in the test catchments differs from that of the areas defining the 100% SCA reflectance. This may be caused by differences in impurities, liquid water content and the age of the snow pack. The SCA products used in this study are not adjusted to overcome that sort of problems. However, new algorithms taken such effects into account are about to be developed, *i.e.* on the Norwegian Computer Centre (NR), and will hopefully improve the satellite SCA product considerably. Studies are also in progress at the University of Oslo using satellite data for estimating surface temperature distribution and include this in snow simulations in the fully distributed ECOMAG model (Motovilov *et al.* 1999).

Our results are quite similar to the results of Johansson *et al.* (2003), Huttunen *et al.* (2005) and Metsämäki *et al.* (2003), and show that updating hydrological models by satellite data can be successful. However, all these studies reveal difficulties in identifying when and where the updating is successful. The model parameters are probably too strongly fitted to the quite few observations of SCA, as stated by Johansson *et al.* (2003), regarding the precision of these data. The lacking ability of simulating less than 100% SCA during days with temperatures below 0°C and fresh snow is another problem to be solved. Use of terrain information and submodels for redistribution of snow may lead to better consistency between SCA observations and simulations.

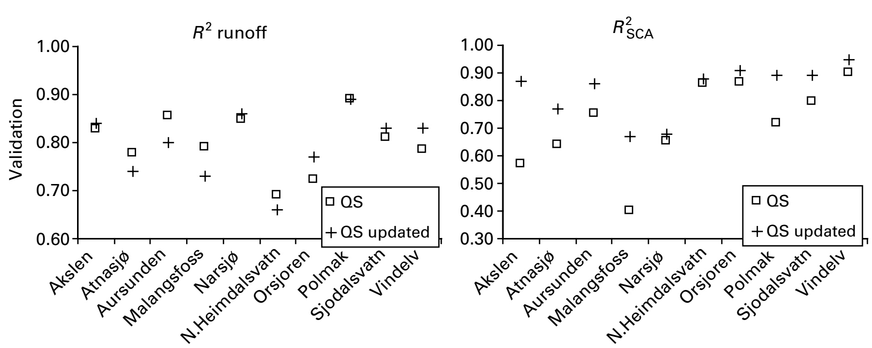

Figure 4 Model performance, based on the Nash–Sutcliffe coefficient R^2, before and after updating model input based on satellite-derived SCA

The studies using the HBV model show less convincing results than those using the SRM model, i.e. Rango *et al.* (2003) and Nagler *et al.* (2004). This could be due to the fact that the studies using the SRM model primarily focuses on simulating the snow cover and runoff in the snow melt period, whereas the HBV models are calibrated to simulate different types of flood events and low flow periods throughout the whole year.

SCA time series

Only AVHRR data was used in the calibrations and in the model updating. MODIS and ASAR data was used as control data afterwards for the 2004 season in order to evaluate if these data could be used in the updating of models calibrated on AVHRR data. The results showed that SCA from ASAR was considerably different from the SCA from MODIS and AVHRR (Figure 5). The radar-derived SCA seemed to overestimate dry snow areas due to the dry snow algorithm and underestimate wet snow areas due to problems with detecting patchy snow. These results are similar to the results in the HYDALP project (Rott *et al.* 2000) and the results by Engeset *et al.* (2003). Figure 5 illustrates the problems of harmonizing SCA from ASAR to the optical data for two cases. In the Akslen catchment SCA was underestimated by the ASAR product compared to the optical data in areas with mixed pixels (snow and bare ground) since these pixels mainly were classified as bare ground in the ASAR product. In the Atnasjø catchment, when little snow was remaining, the dry snow algorithm overestimated SCA in the ASAR product compared to the optical data in the upper areas. Due to these effects ASAR data could not be used to evaluate the hydrological models.

The simulated SCA and the SCA from ASAR, MODIS and AVHRR were lumped together for all eight catchments in southern Norway (Figure 6). The comparison shows that SCA from MODIS and AVHRR were comparable on this scale. The deviation from the simulated SCA was less than 10% for both the optical sensors. The SCA from ASAR was generally too low. A linear transformation on the ASAR data, similar to that on the optical

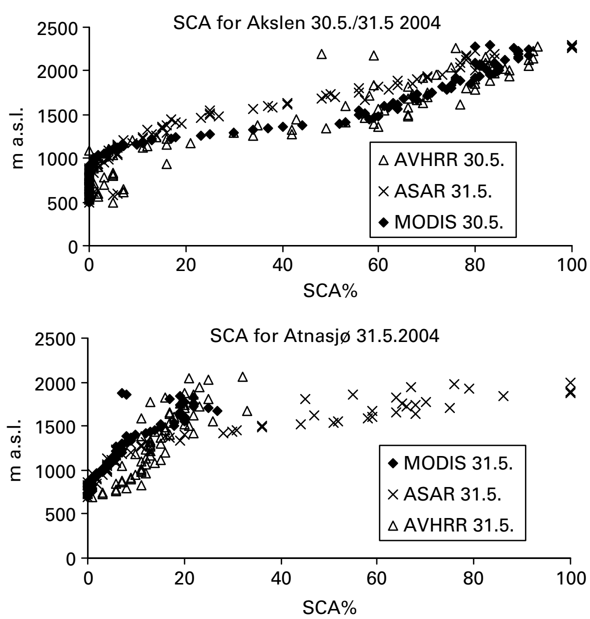

Figure 5 Comparisons of SCA from different satellite sensors (AVHRR, MODIS and ASAR) for the catchments Akslen and Atnasjø. The calculated values are mean values for each 20 m elevation interval in the catchment. Observed SCA for the entire Akslen catchment from the different sensors; MODIS 47.8%, AVHRR 47.8% and ASAR 32.6%. Observed SCA for the entire Atnasjø catchment from the different sensors; MODIS 6.6%, AVHRR 13.4% and ASAR 17.9%

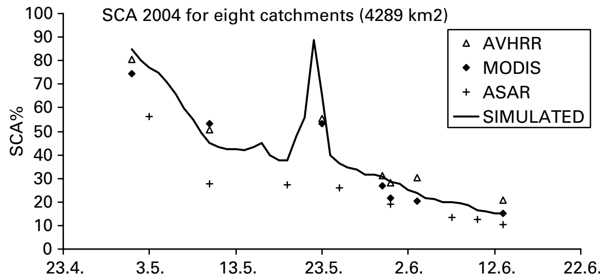

Figure 6 Comparisons of simulated SCA and observed SCA from different satellite sensors (AVHRR, MODIS and ASAR) aggregated for the eight catchments in southern Norway. SCA based on MODIS and AVHRR is transformed in the same way as in the model calibrations to harmonize with the HBV simulations

data, may improve the results. However, overestimation of dry snow and underestimation of patchy snow (Figure 5) indicate that differences between optical and radar SCA cannot be solved by one specific linear transformation for all the different stages in the melt season. ASAR seems to give higher SCA values than optical data in some areas and lower in other areas, depending on the amount of remaining snow.

Rango *et al.* (2004) stated that MODIS provided a logical transition from NOAA-AVHRR data. The results in our study showed that SCA from MODIS corresponded well with SCA from AVHRR. This was also demonstrated by Maurer *et al.* (2003) and Klein and Barnett (2003) in their comparisons between SCA from MODIS and the AVHRR based NOHRSC snow product (Hartman *et al.* 1995), although these studies revealed some differences between the MODIS and the NOHRSC product mainly related to cloud classification and classification of SCA in forested areas.

Conclusions

This study confirmed that the HBV model can be calibrated against SCA as well as runoff, without a major reduction in the accuracy of the runoff simulation. The improved performance in SCA was considerable higher than the loss of performance in runoff. Generally, both the Q and the QS models simulated runoff well in the calibration period. In addition, the QS models showed a good fit to the observed SCA. The QS models revealed possible variations in the quality of the SCA product for the different catchments. Relative flat areas without forests seemed to give the most consistent SCA time series.

Using satellite-observed SCA to update the HBV models showed diverging results, as in other studies. Generally the success was quite random, although a weak tendency of higher success rate at large SCA values was found. This is consistent with the increased uncertainties in satellite SCA products at the end of the snow melt period. Using SCA from satellite images is not straightforward during snow melt, since the spectral signature may vary considerable in space. In order to improve the SCA product during snow melt, information of the snow state could be included in the SCA algorithm.

This study illustrates that satellite-observed SCA in hydrological models can be useful, especially in years with unusual weather conditions. However, in order to use satellite observations of SCA in operational flood warning models, a careful evaluation of each scene and its calculated SCA compared to the stage of snow melt is needed. The evaluation may be formulated as automated rules to determine whether the satellite data should be used for updating or not. Manual inspection of the SCA data is still recommended to avoid erroneous updates.

Furthermore, the study also shows that SCA from the optical sensors, MODIS and AVHRR, are comparable. SCA based on the radar sensor ASAR deviates from the optical SCA. Hence a harmonization of the SCA products is required before integration with the hydrological simulations.

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