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RESEARCH ARTICLE

Uncertainty in satellite remote sensing of snow fraction for water resources management

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Abstract Snow fraction is an important component of land surface models and hydrologic models. Information on snow fraction also improves downstream products retrieved from remote sensing: vertical atmosphere profiles, soil moisture, heat fluxes, etc. The uncertainty of the fractional snow cover estimates must be determined, quantified, and reported to consider the suitability of the product for modeling, data assimilation and other applications. The reflectances of snow and non-snow are characterized by a very significant local variability and also by changes from one scene to another. The local snow and non-snow endmembers are approximated by the Normalized Difference Snow Index with a high accuracy. The magnitudes of snow and non-snow Normalized Difference Snow Indexes are scene-specific and calculated on the fly to retrieve snow fraction. The development of the Normalized Difference Snow Index based algorithms to estimate snow fraction including a scene-specific approach taking local snow and non-snow properties into account is considered an optimal way to fractional snow retrieval from moderate resolution optical remote sensing observations. The Landsat reference data are used to estimate the performance of the fractional snow cover algorithms at moderate resolution and to compare the quality of alternative algorithms. The validation results demonstrate that the performance of the algorithms using Normalized Difference Snow Index has advantages. The advantages achieved in snow fraction retrieval lead to improved estimate of snow water equivalent and changes in snow cover state contributing to better modeling of land surface and hydrologic regime. The success of managing water resources on the whole depends on coordinating described investigations with the works of other researchers developing further enhanced models.

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1 Introduction

The availability of water resources and their dependence on current climatic change are of exceptional significance for river discharge (Elguindi et al., 2005). The hydrologic regime of numerous river basins is driven by snow through a significant part of a seasonal cycle (Bamzai and Shukla, 1999). The estimate of water storage and runoff of water from melting snow is critically important for planning agricultural and other activities depending on water supply (Kumar et al., 2015).

The knowledge on spatial snow distribution is important for numerous theoretical studies and practical applications. The snow cover itself is a surface condition influencing the heat and water balances. Snow information provides insight into the amount of water to be expected from snowmelt available for runoff and water supply (Déry et al., 2005b). The water supply related to seasonal changes in snow accumulation and melting is critically important to manage water resources for irrigational agriculture in several countries (Savooskul and Smakhtin, 2013), but there is a certain gap in our understanding of snow impact on water resources. The estimate of water storage and runoff from melting snow determining temporal changes in river discharge is required to plan water resources (Déry et al., 2005a).

Snow cover influences not only the terrestrial water cycle, but also climate change. Snow cover significantly modifies the exchange of energy between the atmosphere and land surface. Seasonal and interannual changes in snow cover distribution and state affect regional (Ellis and Leathers, 1999; Zaitchik et al., 2007) and global (Cohen and Entekhabi, 2001; Yang et al., 2001) processes far beyond high latitudes. Snow cover alters the atmospheric circulation (Gong et al., 2003), changes soil moisture, the state of vegetation, and summer precipitation (Shukla and Mintz, 1982; Delworth and Manabe, 1988).

Snow extent and fractional snow cover (FSC) are the characteristics of snow cover that need to be used as an input for hydrologic and land surface models. The sub-grid variability of snow within numerical models that simulate the hydrologic or atmospheric surface energy exchange processes calls for knowing the fractional snow cover and its distribution as accurately as possible (Liston et al., 1999). However, the problem of reliable snow cover inhomogeneity parameterization in model cells is far from being solved, which was confirmed in discussions at the recent international Arctic Terrestrial Workshop in Oxford, United Kingdom, September 14–15, 2017.

The snow cover maps, including snow fraction derived from satellite observations present the best possible information relevant to numerous applications, in particular to estimate snow water equivalent (SWE). The current quality of microwave observations does not provide necessary accuracy of data on snow water equivalent. Using snow fraction derived from optical observations is considered the main approach in hydrologic, land surface modeling and data assimilation (Appel, 2014) to estimate snow water equivalent.

Snow fraction presents the most reliable and robust characteristic of subgrid inhomogeneity of snow cover and therefore widely applied in the implementation of the most commonly used tool - snow depletion curve (SDC) - illustrating related temporal changes in snow coverage and snow water equivalent. The snow depletion curve could be obtained from remote sensing or *in situ* observations (Anderson, 1973). This is a very powerful approach to describe changes in snow conditions, employed by many researchers (Déry et al., 2005a; Andreadis and Lettenmaier, 2006; Kolberg and Gottschalk, 2006; Delbart et al., 2015).

In many areas, satellite-based images of snow fraction are by far the best (or even the only) information available on the regional snow cover. Snow fraction is a primary characteristic of snow cover that could be used as input for hydrologic, meteorological and climate modeling. Gaining insight into the snow fraction changes is possible on the basis of physical modeling helping to provide an understanding of processes explaining the evolution of snow state.

Quantitatively estimated snow products are important components of land surface and hydrologic models. Snow fraction, as the percentage of a model cell covered by snow should be a parameter of such models. It is critically important, because snow fraction is a major measure of spatial inhomogeneity of snow cover determining the atmosphere-surface interaction, in particular heat and mass balances.

However, the problem of reliable snow cover parameterization in models is far from being solved. “In a sense, snow is an inherently difficult quantity to model: … errors in snow cover quickly cascade into larger inaccuracies in albedo, soil moisture, energy exchange, and atmospheric conditions” (Zaitchik and Rodell, 2009). The authors, for example, demonstrated that the change of air temperature by several degrees could lead to less significant errors than the influence of snow cover modified by observations.

Numerous works beginning from Liston et al. (1999) illustrated that the quality of hydrologic modeling improves when the information on snow cover is assimilated. The experiments with a snow model using direct measurements of snow (Clark et al., 2006) confirmed the improvement of information on snow distribution along with general hydrologic characteristics.

Though data assimilation for hydrologic studies has a relatively short history, several different approaches have been implemented and tested to translate observations on snow fraction into SWE (Reichle et al., 2002; Salamon and Feyen, 2009; Thirel et al., 2010). Sophisticated schemes of physically based snow assimilation are required to establish the balance between snow state and heat and water fluxes.

Snow depletion curve became a standard tool for snow cover assimilation, taking into account the relationships between snow fraction and SWE. It is considered the best approach when the relationships combine surface observations on snow depth with satellite observations on snow fraction.

Systematic observations on snow fraction provide numerous advantages and therefore are certainly preferable for assimilation schemes. Information on snow fraction could be used to improve our understanding of physical processes and a mathematical description of snow evolution.

The assimilation of snow fraction in land surface models substantially increases the quality of information on snow, including SWE (Zaitchik and Rodell, 2009). There are successful attempts of using information on snow fraction to correct, not only SWE, but also other parameters of land surface models when a locally specific SDC is well defined (Andreadis and Lettenmaier, 2006; Clark et al., 2006). Improved retrieval of snow fraction helping better estimate heat and mass fluxes could be used for assimilation to initiate model calculations as well as to assess the quality of model outputs.

One of the recently realized innovative approaches is based on a simplified data assimilation scheme that “simulates daily changes of SWE, snow depth and water content in grid cells across a region.” (Saloranta et al., 2015). The essence of the approach is the analysis of the discrepancy between calculations of snow fraction and its retrieval from satellite observations using Fourier Amplitude Sensitivity Test (FAST). This test identifies the parameters responsible for the discrepancies and recommends their tuning for better results. The approach provides the best quality of results when several consecutive satellite observations in the region under consideration are available for the same season. The model and its assimilation scheme could be modified according to specific study tasks.

Snow products used for a wide range of different applications, including agricultural and water management, require a quantitative understanding of the errors (Dong and Peters-Lidard, 2010). Comprehensive validation of fractional snow cover is a critically important means to improve retrieval algorithms. The validation procedures are designed to quantitatively estimate the errors in the fractional snow product on the basis of a comparison with high-resolution remote sensing information that is used as an effective source to establish reliable ground truth (Appel, 2012).

Because of a very significant impact of snow cover, it is necessary to improve the quality of snow retrieval from remote sensing. The community needs reliable remote sensing measurements and climate information, in particular on snow fraction, that are well quantified and quality controlled to be effectively used to study changes, trends, and variability in Earth's environment (Key et al., 2013). The accuracy and errors of the fractional snow cover estimates must be determined, quantified, and reported to consider the suitability of the product for hydrologic and land surface models, data assimilation (Appel, 2011a).

The emphasis in this manuscript is put on the development of robust methodologies to estimate the uncertainty in fractional snow cover retrieval and the comparison of the approaches developed by the author with other existing estimates of snow fraction - the questions previously not described in details. Essentially, the manuscript reflects the development related to estimating snow fraction uncertainty that was made after publication (Appel, 2011a) though some aspects of the problem investigated in the paper were discussed before and include references to earlier years.

The quality of fractional snow algorithms was obviously analyzed before and using the high-resolution satellite observations was considered the best approach to estimate the performance of algorithms. In many cases an algorithm under evaluation was applied to high-resolution and moderate resolution observations. The difference between the aggregated fine resolution data and the moderate resolution product was considered as an indicator of the algorithm uncertainty. However such a typical approach to estimate the errors in snow fraction products was not without significant shortcomings. The author of this paper has participated in similar inter-comparison between two fractional snow algorithms under consideration to be implemented with the Visible Infrared Imaging Radiometer Suite (VIIRS). Each of the algorithms was characterized by uncertainty on the order of 0.1, but the difference between snow fractions provided by the two algorithms was usually three times larger than the uncertainties of the algorithms. This is an illustration of a profoundly wrong approach to estimating fractional snow algorithm performance, confirming the significance of the problem under consideration.

The overall objective and the focus of the study is the investigation of the uncertainty in retrievals of snow fraction from remote sensing observations. The uncertainty in this paper is characterized by different statistical parameters determined on the basis of comparing remote sensing information with the Landsat reference data (ground truth). However the role of the uncertainty is not limited by its estimate. The comparison of snow fraction derived from remote sensing information with the reference data serves as a very valuable source of understanding shortcomings in a snow fraction retrieval algorithm and choosing ways to improve its performance. Enhanced knowledge on snow fraction and its uncertainty estimates is beneficial to improving snow model and assimilation schemes on the basis of a better description of underlying surface state for regional high-resolution hydrologic and weather prediction.

The more specific objectives of this study are as follows:

- illustrate the enhancement of the snow fraction retrieval and information on snow cover,
- quantitatively estimate the performance of the fractional snow cover algorithm,
- improve understanding of snow processes to modify models describing snow changes.

In accord with these objectives, the paper begins with a description of moderate resolution satellite snow observations, introduces the Normalized Difference Snow Index (NDSI) and outlines the features of the NDSI-based approach (including its scene-specific version) to estimate snow fraction. The high-resolution satellite observations are recommended as reference information and the comparable analysis demonstrates the advancements of proposed methodology to estimate the uncertainty in fractional snow retrieval and to validate the algorithms performance.

2 The NDSI-based methodology to estimate snow fraction

2.1 Moderate resolution satellite snow observations

Fractional snow cover in this publication is understood to be the viewable snow fraction - one of the most important components of land surface and hydrologic models. Snow fraction - the central subject of the study - represents subpixel percentage of snow cover and therefore differs from Snow Covered Area (SCA) estimated on the basis of aggregating pixels - defined as completely snow free (0%) or snow covered (100%) - for the total area considered.

Remote sensing is a primary source of snow information to answer many research questions, in particular for hydrologic studies. Despite numerous works, microwave remote sensing information on snow water equivalent (SWE) is not accurate enough for many hydrologic applications (Pulliainen et al., 2010). The difficulties of getting reliable descriptions of snow cover features (Tait and Armstrong, 1996; Rodell et al., 2004; Dong et al., 2005; Foster et al., 2005) are summarized by the following statement: “both model predictions and passive microwave snow water equivalent observations contain large errors” (Dong and Peters-Lidard, 2010).

On the contrary, optical (visible and near-infrared) satellite observations on snow are of much better quality (Parajka and Bloschl, 2006) and could be available frequently – up to several times a day in cloud free regions. Optical remote sensing is used to provide the valuable snow information, first of all, snow extent and snow fraction as well as snow properties. Satellite observations could be considered as data presenting an unparalleled source of information for large scale and global applications, including water resource management, and hydrologic and land surface models (Rodell and Houser, 2004; Andreadis and Lettenmaier, 2006; Su et al., 2008; Zaitchik and Rodell, 2009; Bavera and De Michele, 2009; Roy et al., 2010).

The estimates of snow fraction uncertainty are examined at the example of the algorithms developed by the author for the NASA Earth Observing System (EOS) Moderate Resolution Imaging Spectroradiometer (MODIS) and for VIIRS onboard the Suomi National Polar-orbiting Partnership (SNPP) platform (Appel, 2011b). The MODIS observations at a nominal spatial resolution of 500-m are used to derive the fraction of snow cover. The VIIRS observations give the opportunity of snow fraction mapping at 375 m at nadir, which is adequate for most applications. Because of an original scanning and aggregation scheme, VIIRS observations are characterized by a pixel growth factor of only two both along a track and along a scan giving the opportunity of getting imagery globally at 800 m resolution.

The measurements from these sensors could be used for comprehensive studies of snow cover with uncertainty depending on implemented algorithms. The SNPP VIIRS and EOS MODIS instruments have similar characteristics relevant to snow detection, thus the algorithms and snow cover products from the two sensors could be very similar. To achieve the highest quality and resolution of optical moderate resolution satellite observations, the simulated VIIRS proxy data were carefully generated on the basis of reprocessing MODIS measurements for 2–9 February 2003 (Appel, 2014) specifically for cryosphere studies.

Such an enhanced approach combines the best available radiometric calibration (MODIS) with the lowest pixel growth factor both along a track and along a scan (VIIRS) giving the opportunity of getting spatially detailed imagery globally at 800 m resolution and 375 m at nadir. The set of these VIIRS observations included in this publication makes the results comparable with previously fulfilled studies.

2.2 Normalized difference snow index

The fact that snow reflectance is high in the visible wavelengths (0.4–0.7 μm) and very low in the near-infrared region (0.8–2.5 μm) distinguishes the snow cover from other land surface types in almost all cases.

This clearly explains why a central feature of the MODIS and the VIIRS snow algorithms is the Normalized Difference Snow Index, a term coined in (Hall et al., 1995) having a long and impressive heritage (Crane and Anderson, 1984; Dozier, 1989).

The MODIS band 4 (0.555 μm) and band 6 (1.64 μm) as well as VIIRS imagery bands I1 (0.640 μm) and I3 (1.64 μm) correspond to the visible wavelengths and the near-infrared region used to calculate NDSI (Table 1 and Fig. 1).

The combination of the MODIS band 4 and band 6, or VIIRS band I1 and I3 are used in NDSI traditionally calculated from top of the atmosphere (TOA) reflectances:

$$\mathrm{NDSI} = (\mathrm{b4} - \mathrm{b6})/(\mathrm{b4} + \mathrm{b6}), \quad (1)$$

or

$$\mathrm{NDSI} = (\mathrm{I1} - \mathrm{I3})/(\mathrm{I1} + \mathrm{I3}), \quad (2)$$

where b4 and b6 are the MODIS reflectances for bands 4 and 6; I1 and I3 are the VIIRS reflectances for imagery bands 1 and 3.

The Normalized Snow Difference Index characterizes the distinction between the reflectance in the visible wavelengths and the reflectance in the near-infrared wavelengths. NDSI presenting relative ratio of reflectances to a large degree suppresses the influence of varying illumination conditions, atmospheric effects and viewing geometry. It is widely considered as an indicator of the presence of snow on the ground and used as the basis of “SNOWMAP” approach (Klein at al., 1998) system-

Table 1 Snow fraction sensor input for MODIS and VIIRS

Sensor	Band	Wavelength range/μm	Central wavelength/μm	Sub-satellite FOV[a)]/km
MODIS	4	0.545 – 0.565	0.555	0.50
	6	1.628 – 1.652	1.64	0.50
VIIRS	I1	0.60 – 0.68	0.64	0.375
	I3	1.58 – 1.64	1.61	0.375

a) FOV: field of view.

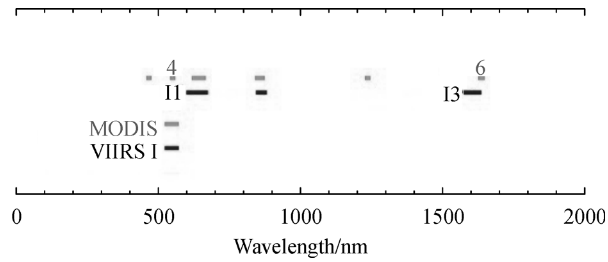

Fig. 1 Wavelength locations of the MODIS and VIIRS bands. Bands used in the NDSI calculations are labeled with band number.

atically used in NASA for binary (snow vs non-snow) pixels classification.

2.3 NDSI-based approach to fractional snow cover retrieval

The reflectances of snow and non-snow are characterized by a very significant local variability (Fig. 2) within both moderate resolution VIIRS scenes and small regions of high–resolution Landsat observations. In such a typical example the X axis corresponds to reflectance for visible VIIRS or Landsat band and the Y axis corresponds to reflectance for near-infrared VIIRS or Landsat band.

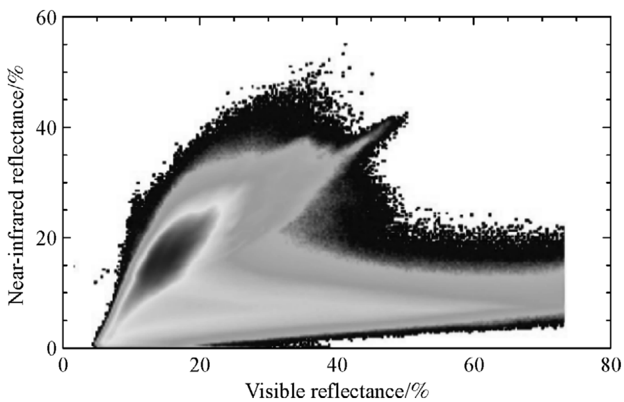

Fig. 2 Two dimensional probability density of pixels in spectral space defined by visible (X axis) and near-infrared (Y axis) reflectances (%).

The approach proposed by Salomonson and Appel (2004) for fractional snow cover derivation is based on the concept that NDSI is sensitive enough to provide the snow fraction and can be used to express the range in the spectral differences between the non-snow covered background (0% snow fraction) and complete snow cover (100%). The approach further utilizes the hypothesis that the gradations of NDSI between "end points" (0% snow cover and 100% snow cover) are related to the fraction of snow cover in each VIIRS pixel.

In other words, the essence of the approach is in the assumption that pixels with identical NDSI have equal snow fractions. It is important to note that the pixels corresponding to a specific NDSI magnitude are located on a straight line in the scatter plot defined by the reflectances used to calculate NDSI.

Figure 2 representing the two-dimensional probability densities of pixels in the space defined by visible and near-infrared reflectances is characterized by two loci of pixel concentration. The first one with low visible reflectance and high near-infrared reflectance corresponds to snow free area, the second one with high visible reflectance and low near-infrared reflectance represents snow. The analysis of the probability densities shows that the same reflectances could correspond to non-snow and snow. This statement is correct for both visible and near-infrared reflectances, clearly proving that directly using reflectances for estimates of snow fraction could lead to large errors.

The most probable locations of snow and non-snow in the spectral space (Fig. 2) are characterized by the NDSI corresponding to 100% and 0% of snow fraction. Pixels between these extreme magnitudes have intermediate snow fraction determined by interpolation between the extreme NDSI values.

The approach to NDSI-based snow fraction retrieval developed by Salomonson and Appel (2004) linearly relates fractional snow cover (FSC) to the observed NDSI

$$\mathrm{FSC} = a + b^{*}\mathrm{NDSI}, \tag{3}$$

where $a = -0.01$, $b = 1.45$.

Later it was demonstrated (Salomonson and Appel, 2006) that the NDSI-based approach could be extended to the Aqua MODIS if reflectance in band 7 (b7) centered at 2.13 μm is used instead of band 6 that had many nonfunctional detectors. Because the reflectances acquired in that band are markedly lower than in the 1.64 μm region and therefore are characterized by smaller signal to noise ratio, additional validation using NDSI7

$$\mathrm{NDSI7} = (\mathrm{b4} - \mathrm{b7})/(\mathrm{b4} + \mathrm{b7}), \tag{4}$$

was required.

2.4 Variability in NDSI endmembers between scenes

It is necessary to emphasize that there are two quite dissimilar types of reflectance variability. Both of them should be taken into consideration. The local variability within a scene considered in the section 2.3 is approximated by constant values of NDSI (endmembers) for snow and non-snow.

Our analysis of data for the scenes under consideration confirms that a majority of remote sensing observations could be reproduced by two-endmember models. But those endmembers vary from scene to scene – the second type of variability that needs to be taken into account as follows.

In a general case, the relationship between NDSI and snow fraction should depend on the characteristics of snow and non-snow endmembers. The quality of fractional snow retrieval could be improved if the variability of properties characterizing snow and underlying non-snow states is taken into consideration. Allowing for the variability in endmembers (spectral signatures or NDSI) is a key requirement to fractional snow cover algorithms.

Very large changes in predominant reflectances characterizing different snow and underlying non-snow surfaces for the scenes with relatively good illumination for the sun elevation within the range of 24°–36° are illustrated by Fig. 3 in the same spectral space as Fig. 2. If such a variability of reflective properties is taken into account, the quality of snow retrieval could be improved.

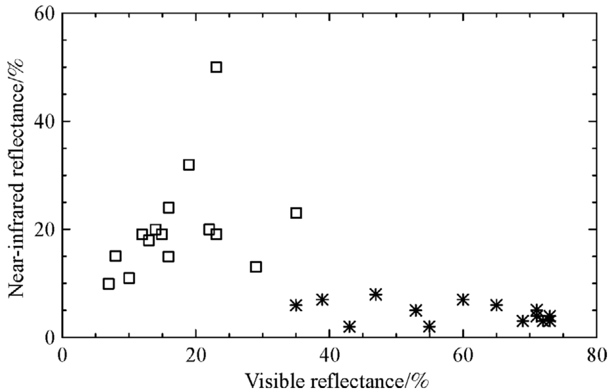

Fig. 3 The most probable snow (asterisks) and non-snow (squares) VIIRS reflectances for 16 scenes under consideration.

2.5 Scene-specific NDSI approach to snow fraction retrieval

It was expected that the NDSI-based approach could be adjusted or ''tuned'' for specific areas such as watersheds or regions and subsequently increase the accuracy of the fractional snow-cover estimates.

Even though the Eq. (3) with fixed coefficients *a* and *b* provided valuable results, it is clear that improvements for specific areas are possible. For example, based on the NDSI approach and using results from (Salomonson and Appel, 2004), improved fractional snow cover estimates over the Kuparuk watershed were achieved by suitably adjusting the snow cover algorithm for that specific area (Déry et al., 2005a).

The optimal statistical relationships between snow fraction and NDSI can and do vary from region to region as well as from day to day (Salomonson and Appel, 2004, 2006). It was mentioned in these studies that more improvements in the fractional snow cover algorithm should be pursued to better account for variability in specific local conditions.

Previous works of the author demonstrated that more accurate information on snow cover could be retrieved from remote sensing measurements when specific features of a region and a time/date of measurements - snow and background surface types, the geometry of satellite observations, the state of the atmosphere - are taken into consideration. The changes in snow and non-snow reflective properties influence algorithm parameters that could be adjusted to local conditions of observations. This was strong motivation for the further improvement of the NDSI-based algorithm.

In general, the relationship between NDSI and snow fraction should depend on snow and non-snow NDSI endmembers. The quality of snow retrieval could be improved if the variability of snow and underlying non-snow properties is taken into account. Allowing for the variability in spectral signatures or NDSI characterizing endmembers is a key requirement to fractional snow cover algorithms.

Improved fractional snow cover retrieval can be achieved by an algorithm employing scene-specific local properties of snow and non-snow endmembers estimated from the analysis of the NDSI histogram (probability density function) identifying predominant magnitudes of snow and non-snow NDSI endmembers (Fig. 4).

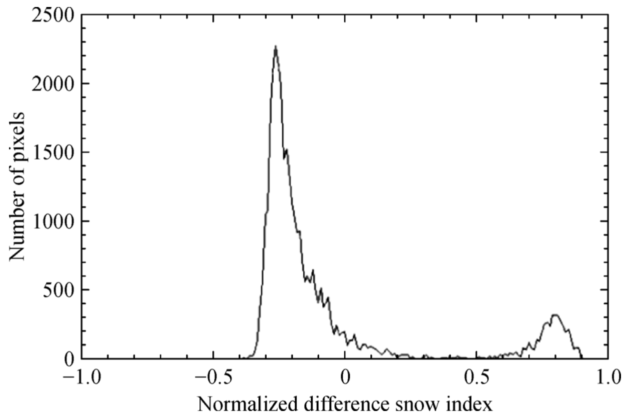

Fig. 4 Example of NDSI probability density function.

The adjustment of the parameters in the NDSI-based snow algorithms to specific local conditions (Fig. 3) is a promising improvement leading to better quality of the VIIRS snow products.

It is not a simple task to predetermine changes of parameters in Eq. (3) to describe scene-specific conditions. Therefore the relationship between snow fraction and

NDSI has been modified as follows.

$$\mathrm{FSC} = \frac{\mathrm{NDSI} - \mathrm{NDSI}_{\text{non-snow}}}{\mathrm{NDSI}_{\text{snow}} - \mathrm{NDSI}_{\text{non-snow}}}, \quad (5)$$

where $\mathrm{NDSI}_{\text{snow}}$ and $\mathrm{NDSI}_{\text{non-snow}}$ are NDSI characterizing snow and non-snow endmembers.

The adjustable version of the algorithm can and do vary from region to region and from time to time depending on snow and background surface state as well as on the viewing and observation geometry. To increase the accuracy of the algorithm for operational applications, we assume variation of the endmembers on a pixel-by-pixel basis, which accounts for variation in surface types both for snow and non-snow endmembers.

3 Uncertainty in satellite remote sensing of snow fraction

3.1 Using high-resolution reference data as ground truth

Developing a fractional snow cover algorithm requires a source of ground truth. After considering various possibilities of utilizing high-resolution satellite data, it was decided that the Landsat observations would be readily available, suitable and effective. Data from Landsat satellites are extensively used to enhance and validate snow fraction retrieval. Those high-resolution data playing a very important role in the studies are considered as reference information or ground truth for moderate resolution MODIS and VIIRS observations.

There is no agreed-upon methodology to use high-resolution satellite observations to validate the quality of moderate resolution algorithms retrieving snow fraction.

An approach to process high-resolution observations to estimate the performance of MODIS and VIIRS fractional snow cover products described here was created simultaneously with the development of the NDSI-based fractional snow algorithm and implements the following specific steps.

• Select matched in time moderate resolution and high-resolution observations collected on the same day preferably with time separation of less than an hour.

• Binary classify high-resolution Landsat 30-m pixels as snow or non-snow (Fig. 5) using the ‘‘SNOWMAP’’ approach to identify snow-covered pixels versus those not covered by snow. The Landsat bands (0.55-μm band 2 and 1.64-μm band 5) are used to calculate NDSI values.

• Co-register data sets to make high-resolution and moderate resolution information easily comparable.

• Aggregate classified high-resolution pixels within cells of a relatively coarse predetermined grid to reduce the effect of data spatial mismatch. For each grid cell, the snow fraction is determined on the basis of the Landsat observations by counting the number of Landsat pixels

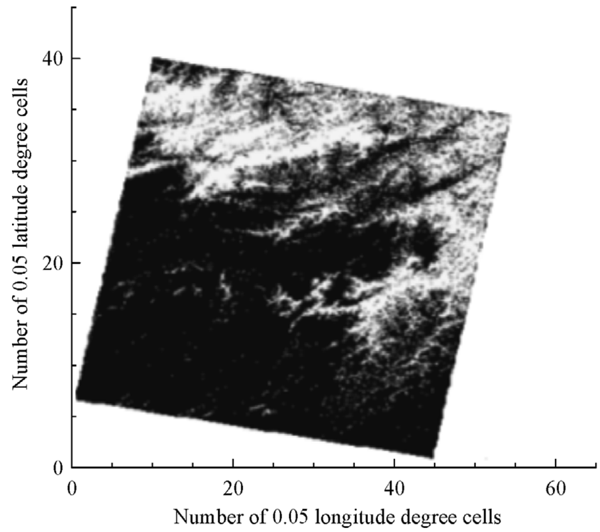

Fig. 5 Landsat binary snow cover classification.

covered by snow versus the total number of Landsat pixels in the cell.

• Calculate NDSI and snow fraction based on moderate resolution observations in each cell. Bilinear interpolation is used to provide reflectances corresponding to grid cell centers.

• Compare snow fraction derived from high-resolution classifications with moderate resolution fraction estimates.

The moderate resolution data are processed on the basis of a fractional snow cover algorithm to be developed or validated. It requires extensive works on the algorithm implementation and processing for validation.

3.2 Estimating uncertainty for algorithms developments

Using the measures of snow fraction within 500-m cells as provided by Landsat, statistical linear relationships between the NDSI from MODIS observations and the true fraction of snow-cover from Landsat at 500-m resolution were initially derived for the areas covering a wide variety of snow-cover conditions. A MODIS land/water mask was employed to exclude lakes, etc., from consideration.

An ordinary least-squares (OLS) linear regression between snow fraction and NDSI corresponding to the 500-m grid cells was derived. But the used approach was not common, because the dependence of NDSI on snow fraction was studied instead of traditional calculations of snow fraction as a function of NDSI. Such a reversed approach is not new. The analysis of two reversed calculations is related to the ‘‘errors-in-variables’’ problem. However in the specific case under consideration, there is another important feature. The FSC on NDSI analysis minimizes the variance of FSC relative to the regression line extending for values of FSC above 1.0 and below 0.0 while the analysis of NDSI on FSC inherently constrains the minimizing of NDSI variance over a range of FSC between 0.0 and 1.0.

Because of this circumstance, the regression of NDSI on snow fraction provides a more accurate linear relationship used to calculate snow fraction after the inversion of the relationships. The inverted relationship shows a better visual fit to scatter plots of fraction versus NDSI than a traditional regression and characterized by smaller errors.

The regression equations for each of the scenes provide optimal estimates of the NDSI-based algorithm for individual scenes. The application of the regression equations to other scenes presents independent validation of the stability and robustness of the approach under consideration. The results demonstrate that the relationships hold up quite well (Table 2): a mean absolute error is consistently well below 0.1 and a standard deviation close to 0.1.

The tasks addressed in (Salomonson and Appel, 2006) included validation efforts to show that fractional snow relationships work well for both Terra and Aqua MODIS instruments when compared to Landat-7 Enhanced Thematic Mapper ground-truth observations covering a substantial range of snow cover conditions.

As the first step in development of the algorithm for Aqua it was considered natural to compare the regression of fractional snow cover on both NDSI and NDSI7 at the example of the Terra MODIS data providing reliable information on both reflectances.

The regression equations from several images were averaged and also applied to independent data from other regions. However the approach to calculation regression relationships was modified again.

New criteria for cells analysis were examined and only cells with snow fraction above 0.1 and below 0.95 were taken into consideration to develop statistical relationships of snow fraction with NDSI and NDSI7. The improved criteria to select cells give better visual fit in the scatter plots of fractional snow cover vs NDSI. It should be noted that the relationships of snow fraction versus NDSI and NDSI7, developed for the limited range 0.1–0.95 of fraction magnitude, were used to estimate the fraction of snow in 500-m pixels over the entire range from zero to 100% snow fraction.

There is another important circumstance to be taken into account analyzing statistical regression results. The correlation coefficients became lower when the limited 0.1–0.95 range is used, but the root-mean-square (RMS) error also reduced, which diminished uncertainty despite lower correlation coefficient. Such changes are related to not using the high number of points clustered around 100% snow cover in the correlation.

The results of testing average regressions (named “universal” relationships)

$$\mathrm{FSC} = -0.01 + 1.45\ \mathrm{NDSI}, \tag{6}$$

$$\mathrm{FSC} = -0.64 + 1.91\ \mathrm{NDSI7}, \tag{7}$$

at the example of independent data are shown in Tables 3 and 4 for the Terra MODIS and in Table 4 for the Aqua MODIS.

Over all the scenes used to independently validate the relationships, the correlation coefficients were near 0.9 and ranged from 0.88 to 0.96. The corresponding RMS error values were near 0.1 and varied from 0.04 to 0.13. When tested on scenes where both instruments observed the same conditions at about the same time (separated by a nominal 3 h), the results were similar, but there could be seen some advantage to the Terra MODIS observations (Table 4) characterized by correlation coefficient 0.96 and lower RMS error (0.04–0.07).

The Eqs. (6) and (7) were employed in the Collection 5 of reprocessing Terra and Aqua MODIS data for the entire period of their observations prior to January 1, 2017.

The NASA snow team (I. Appel, D. Hall, G. Riggs) found that the optimal values of a and b for MODIS are applicable to the VIIRS fractional snow cover Environmental Data Record (EDR) algorithm. The relationship were adapted from the MODIS algorithm. The techniques and products were successfully tested and recommended for VIIRS data processing in Joint Polar Satellite System (JPSS).

The Landsat data set of almost 500 scenes was used (Nagler, 2016) to validate different snow cover algorithms. 425 of the Landsat images were available to validate the Terra MODIS fractional snow product.

The validation of “universal” fractional snow algorithm for those scenes demonstrated that the algorithm has advantages in comparison with other snow products. Both on open land and in forested areas for two different reference data sets - created using the techniques described above and on the basis of the Snow Covered-Area and Grain size (SCAG) algorithm - the uncertainty in the NDSI-based retrieval of snow fraction is characterized by the lowest RMS error when compared with other products.

It is of significant interest that the unbiased RMS error of the MODIS fractional snow cover product is noticeably lower in comparison with other products in mountainous regions, including forested mountains.

Table 2 Performance of averaged relationship for two regions tested on a third region

Region	Mean snow cover	Version of model	Mean absolute error	RMS error	Correlation coefficient
Alaska (A)	0.73	R + L	0.04	0.09	0.98
Russia (R)	0.56	A + L	0.08	0.13	0.97
Labrador (L)	0.64	A + R	0.06	0.11	0.96

3.3 Methodology of snow fraction validation

The previously described estimations of the "universal" NDSI-based algorithm show that on average there is no bias between calculated and true values of snow fraction, which indicates that improving the results of calculations is possible only when varying modifications of the NDSI algorithm are implemented for individual scenes.

It has been assumed that for particular areas, the results will be improved in comparison with "universal" Eq. (3) if the relationship between NDSI and snow fraction is adjusted for specific conditions of observations. Such improvements should be expected (Appel, 2015a), because the "tuning" takes better account of the particular non-snow covered terrain and the snow-covered areas.

The uncertainty in snow fraction retrieval for VIIRS is analyzed for 0.05° cells of a latitude/longitude grid often used for hydrologic and climate modeling (Fig. 6).

The aggregation of retrieved snow fraction within 0.05° Climate Modeling Grid (CMG) cells provides the assessment of snow fraction for the part of a cell not obscured by cloudiness. Only pixels with solar zenith angles not more than 85° are taken into account. Gridded snow data combine all pixels classified as land (including desert), even those where cloud shadow, fire, heavy aerosol, or cirrus were detected by upstream algorithms. Other pixels - inland water, sea water, and coastal - are excluded from the analysis.

In addition to calculating the characteristics of retrieved snow fraction, the quantitative evaluation of fractional

Table 3 Testing "universal" relationship for Terra for independent scenes

Region	Mean snow cover	RMS error	Correlation coefficient	Regression on ground truth
Kuparuk	0.41	0.13	0.89	−0.02 + 1.05*GT
South America	0.18	0.11	0.93	0.01 + 1.12*GT

Table 4 Testing "universal" relationship for Terra (first lines) for independent Terra scenes and "universal" relationship for Aqua (second lines) for independent Aqua scenes

Region	Mean snow cover	RMS error	Correlation coefficient	Regression on ground truth
Idaho	0.18	0.07	0.96	0.01 + 1.00*GT
		0.10	0.92	0.02 + 0.99*GT
Sierra 1	0.05	0.04	0.96	0.00 + 1.02*GT
		0.07	0.88	0.01 + 0.84*GT
Sierra 2	0.09	0.05	0.96	0.00 + 1.00*GT
		0.09	0.88	−0.01 + 0.85*GT

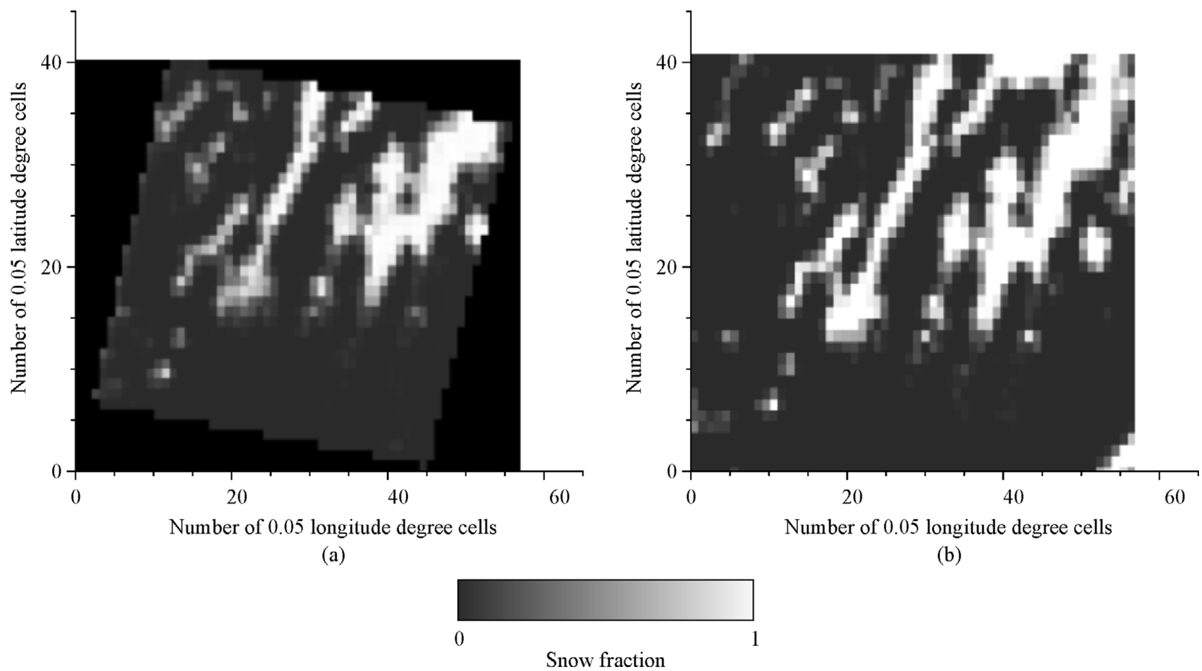

Fig. 6 Aggregated and co-registered fraction data at 0.05° cells of a latitude/longitude grid. (a) Landsat fraction; (b) VIIRS fraction.

snow cover is made, including the regression of the retrieved fraction values on ground truth (Appel, 2015c).

3.4 Results of snow fraction validation

The values of the VIIRS snow fraction retrieved on the basis of the scene-specific linear dependence on NDSI are validated by comparison with high-resolution Landsat observations. The set of 16 Landsat scenes (Table 5) for a wide variety of the transitional zones from snow to snow free areas in quite different environmental conditions is considered as representative data for reliable validation of moderate resolution fractional snow products.

The evaluation of the VIIRS fractional snow cover product as well as other similar products includes the analysis of the fractional snow cover algorithm robustness under varying conditions, in particular within a diurnal cycle for varying geometry of observations, first of all, solar and satellite zenith angles. The consistency of scene-to-scene retrieval could serve as a good indicator of algorithm robustness.

Results of comparison with Landsat information for 16 scenes (Appel, 2014) demonstrate a high accuracy of VIIRS snow fraction estimates (Table 5).

The following is a brief summary of quantitative assessment of the NDSI-based scene-specific fractional snow cover algorithm performance:

- average regression coefficient is 93% despite a couple of low magnitudes;
- average intercept of linear regression line is less than 1% (negative);
- average slope of linear regression line is 0.98;
- average bias of data is less than 1%;
- average standard deviation is 10%.

3.5 Stratified performance of fractional snow cover algorithm

The validation of the VIIRS fractional snow algorithm also includes the analysis of its stratified performance (Fig. 7) for the range 0.1–0.9 of ground truth fraction. Comparison of fractional ground truth (*X* axis) with the results of the NDSI-based algorithm (*Y* axis) is illustrated for 10% intervals of ground truth. Figure 7 shows calculated averaged snow fractions (thick lines) for the intervals and trends (thin lines) for intermediate fractions presenting stratified performance for individual scenes. Because the standard deviation varies between 4% for snow coverage close to 0% or 100% and 14% for snow fraction in the range 40%–60%, the uncertainty of snow fraction retrieval for entire areas covered by snow will be less than 10% even before any further modification or enhancement.

4 Comparison of different approaches to estimate uncertainty of algorithms performance

4.1 Alternative techniques to estimate algorithms

The NDSI-based fractional snow algorithm was not the first developed to retrieve snow fraction and the results provided by other existing algorithms were also estimated.

Within the frameworks of this paper it seems natural to consider some of the techniques used to estimate the uncertainty of fractional snow cover retrievals. Several remote sensing algorithms mentioned in (Salomonson and Appel, 2004) had been applied to retrieve and estimate the

Table 5 Statistics of VIIRS snow fraction validation

Date	Path	Row	Corr. coeff.	Intercept	Slope	Mean true	Mean VIIRS
33	123	32	0.87	−0.09	1.02	0.20	0.11
33	139	29	0.95	−0.03	0.97	0.40	0.36
33	139	30	0.95	−0.07	1.06	0.61	0.57
33	139	31	0.97	−0.01	1.00	0.20	0.19
34	41	33	0.98	−0.01	0.92	0.20	0.18
34	41	34	0.96	−0.01	1.02	0.07	0.06
34	146	29	0.94	−0.03	1.06	0.68	0.68
35	137	29	0.95	−0.03	1.00	0.52	0.49
35	137	30	0.96	0.01	0.94	0.35	0.34
35	153	39	0.78	−0.01	0.65	0.05	0.02
36	128	30	0.90	0.08	0.93	0.92	0.94
37	30	28	0.94	0.24	0.78	0.80	0.87
39	44	27	0.95	−0.01	1.04	0.19	0.18
39	44	31	0.91	0.03	1.07	0.22	0.26
40	156	35	0.96	−0.01	1.06	0.09	0.09
40	156	37	0.94	−0.05	1.18	0.27	0.26

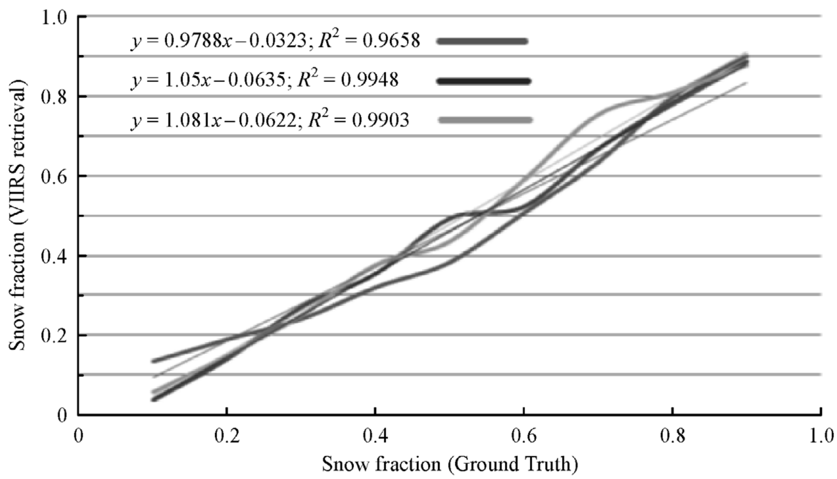

Fig. 7 Stratified quantitative assessment of NDSI-based algorithm performance.

fractional snow cover within a sensor pixel (Nolin et al., 1993; Rosenthal and Dozier, 1996; Barton et al., 2001; Kaufman et al., 2002; Vikhamer and Solberg, 2003; Painter et al., 2003). The publication of Kaufman et al. (2002) is used here for detailed consideration because it, in particular not only estimates the performance of a proposed algorithm, but also compares its quality with another algorithm.

The algorithm proposed in (Kaufman et al., 2002) was applied by the authors to one Landsat image, which supposedly makes the estimate of its quality difficult because of absence of the ground truth for 30 m pixels. The algorithm itself is not analyzed here, the attention is paid only to the validation of its results. First of all, it is necessary to emphasize that the algorithm includes an empirical correction. Similar corrections are not an unheard of technique and could be applied to parameterize the influence of factors not explicitly described by an algorithm.

However, the correction included in the algorithm under consideration is based on the comparison between the results of the approach proposed in (Kaufman et al., 2002) and the snow fraction derived in (Rosenthal and Dozier, 1996) for the same Landsat scene.

In other words, this correction modifies the results to make them close to the snow fraction retrieved in (Rosenthal and Dozier, 1996). It is assumed by the authors (Kaufman et al., 2002) that such a correction is permissible because the technique used in (Rosenthal and Dozier, 1996) had been validated. But the comparison of results from different algorithms - cross-comparison - could not be a criterion of an algorithm's quality, and cannot be considered as appropriate validation.

Such empirical corrections differ from one scene to another because of a wide variety of local conditions and influencing factors. This circumstance precludes using the correction from (Kaufman et al., 2002) for other scenes, unless the correction is validated on the basis of using ground truth information.

The demonstration of "very good agreement … for the empirically corrected data" with the results of the method used to create the correction could not be considered as a proof of the proposed algorithm quality (Kaufman et al., 2002) even when the errors calculated for four quadrants of the single Landsat image used to develop the correction are similar. The average absolute errors of the magnitude between 1% and 2% are calculated in four quadrants using comparison between corrected snow fraction and the results of the algorithm (Rosenthal and Dozier, 1996) used for correction. The average absolute error between 1% and 2% represents the accuracy of approximating the difference between results of two algorithms, but not the algorithm uncertainty.

It is quite appropriate to emphasize that the analysis of the uncertainty characteristic for various existing fractional snow retrieval algorithms indisputably shows that the average absolute error in snow fraction retrieval less than 2% is an underestimate. Such low errors are unachievable, at least unless some special approach to create so called ground truth is implemented. In fact, the special approach is widely used by numerous authors of various fractional snow cover algorithms and therefore needs particular attention.

The essence of this approach to estimate the uncertainty of fractional snow retrieval is the comparison of the results provided by the same algorithm to the same image at different resolutions. It should be emphasized that the validity of such an estimate of the algorithm uncertainty is very doubtful, because performance of practically any algorithm will be excellent if estimated by this "methodology." The criticized approach was successfully applied in (Kaufman et al., 2002) and it does not matter whether the results of corrected or an original algorithm were tested.

The specifics of the approach are well known and described as follows: “1) The algorithm was applied to the original image with a resolution of 30 m to derive the snow fraction, then the resolution of the product was reduced to a 500 m resolution by averaging 17×17 pixels. 2) In the second application, the image resolution was reduced, by averaging the spectral radiance to 500 m and the snow detection algorithm was then applied.” It is not surprising that the differences in snow fraction between those two applications of the same algorithm to the same data “do not exceed 1 or 2 percent.” This consistency check has absolutely nothing to do with the estimate of a fractional snow cover algorithm performance. It is not even a cross-comparison between algorithms, but could be named auto-cross-comparison providing unrealistically low magnitudes of the algorithm uncertainty. Unfortunately, this so called validation of fractional snow data is used by several different authors of fractional snow algorithms. The only possible explanation for implementing such an approach is the intention to artificially increase the quality of algorithm performance. Such an explanation is not worthwhile to be considered in this special issue.

4.2 Comparing fractional snow cover algorithms

It seems very natural that any given surface type within an individual scene exhibits spectral variability. There are numerous reasons (first of all, varying viewing and solar geometry, surface inclination and exposition, terrain morphology, the contribution of direct and diffuse radiation) influencing changes in spectral signatures, but these changes could not be reliably simulated (Appel, 2015b). In this regard, the NDSI approach has obvious advantages because it does not require to study or even consider local reflectance variability parameterizing it by a single characteristic - NDSI.

The advantage was demonstrated by the comparison of the NDSI-based fractional snow algorithm (Salomonson and Appel, 2004) with the techniques used by Kaufman et al. (2002) and Barton et al. (2001). The three approaches were applied to the independent MODIS data that were not used to create the relationship of snow fraction with NDSI. Exactly identical methods to estimate the algorithms performance led to the results shown in Table 6.

It can be seen that the NDSI-based relationship produced statistics that were generally better than the other two methods, with the mean absolute error in particular showing better performance.

The comparison of uncertainties in the results of fractional snow retrieval provided by various algorithms is a reliable way to estimate the quality of different methods. The analysis of spatial distributions illustrating the results of snow fraction calculations on the basis of several algorithms is another convincing way to demonstrate the difference between their outputs.

The maps of fractional snow cover created on the basis of the three approaches under consideration (Fig. 7 in Salomonson and Appel (2004)) illustrated the advantages of the NDSI-based algorithms in comparison with the other two techniques tending to overestimate snow-cover fraction at the low values (snow fractions over large regions where snow is not present) and underestimate snow cover where there is 100% or nearly 100% snow cover as, for example, should be expected at the top of mountain ranges. The overestimate of snow fraction over areas without snow provides false snow retrieval, which is a very noticeable error that should initiate and stimulate the improvement of algorithms giving false snow.

Another impressive demonstration of the advantages characteristic to the NDSI-based fractional snow retrieval is the following comparison with the method using a linear relationship between snow fraction and visible reflectance (tie-point algorithm).

The comparison of the two approaches was made under completely comparable conditions for 16 VIIRS images corresponding to Landsat scenes included in Table 5 without using any predetermined information about the scenes.

Linear relationships of snow fraction with visible reflectance (Fig. 8(a)) and the Normalized Difference Snow Index (Fig. 8(b)) were created using the regressions of ground truth snow fraction on both visible reflectance and NDSI.

The study of the approaches under consideration on the basis of constructing the best linear regressions for each individual scene allows direct comparison of optimal relationships for the algorithms.

Table 6 Comparison of results provided by the NDSI-based algorithm with the methods proposed by Barton and Kaufman for independent validation

Region	Method	Mean snow cover	Mean absolute error	RMS error	Correlation coefficient
Kuparuk	Barton	0.33	0.14	0.19	0.93
	Kaufman	0.36	0.11	0.15	0.93
	NDSI	0.41	0.08	0.12	0.95
South America	Barton	0.18	0.10	0.13	0.95
	Kaufman	0.22	0.07	0.10	0.96
	NDSI	0.21	0.04	0.10	0.97

Such a non-traditional analysis provides the opportunity to compare potential optimal versions of the alternative algorithms simply using the correlation tools without the influence of possible different methods to estimate the endmembers.

The calculated linear regressions on NDSI (correlation coefficients of 0.95) have obvious advantages when compared to the calculated linear regressions on the visible reflectance (correlation coefficients of 0.85). There is 60% increase in the standard deviation (100% in variance) for the regressions on visible reflectance (Fig. 9) in comparison with the standard deviation for the regressions on NDSI.

The results in this section illustrate the performance of several different fractional snow algorithms under completely comparable conditions. The validation results demonstrate that, on the whole, the performance of the NDSI-based algorithms has significant advantages.

4.3 Enhanced description of fractional snow cover changes for water management

Snow cover is an important factor influencing hydrologic processes and fractional snow cover is a main characteristic of subgrid inhomogeneity that is essential for numerous water management applications. Changes in snow fraction are most pronounced after beginning of snow melting, influencing estimates of river discharge as well as modeling and prediction of thermodynamic interaction between the atmosphere and underlying surface. The uncertainty in estimates of snow fraction directly influences those water management applications, in particular created for agriculture.

The significance of the information on the fractional snow uncertainty increases noticeably for snow assimilation into models - the technique directly using information on snow fraction uncertainty. The careful analysis (Kumar et al., 2015) clearly demonstrated the advantages of using MODIS snow data retrieved on the basis of the NDSI-based approach in comparison with the Interactive Multi-sensor Snow and Ice Mapping System (IMS) traditionally used in NOAA. The results of "snow data assimilation in the Noah land surface model … indicate that the use of MODIS data is effective in obtaining added improvements … whereas the impact of IMS data is small" (Kumar et al., 2015).

The analysis of results provided by models with snow data assimilation goes far beyond the goals of this publication. However the author's experience could serve as a convincing illustration of several important points included into consideration in the present work. The advantages of using fractional snow cover information are demonstrated with his participation at the example of applying snow areal depletion curves inferred from MODIS observation to the catchment based land surface model (CLSM) for numerical simulations of hydrometeorological processes (Déry et al., 2005a).

A brief summary of the important achievements using some quotes from the work is as follows.

1) A subgrid-scale snow parameterization has been developed.

2) MODIS snow areal depletion curves during the spring transition period exhibit similar features to those derived from surface-based observations.

3) It has been demonstrated that remote sensing data could be used for a simple subgrid-scale snow parameterization that includes a deep and a shallow snow cover fractions.

4) It is shown that persistent snowdrifts associated with a secondary plateau in the snow areal depletion curves, are hydrologically important.

5) An automated method is developed to generate the shallow and deep snow cover fractions from MODIS snow areal depletion curves.

6) The developed methodology provides the means to apply the subgrid-scale snow parameterization in all watersheds subject to seasonal snow cover.

7) Simulations with and without the subgrid scale snow parameterization illustrate the benefits of incorporating snow fraction into the simulations.

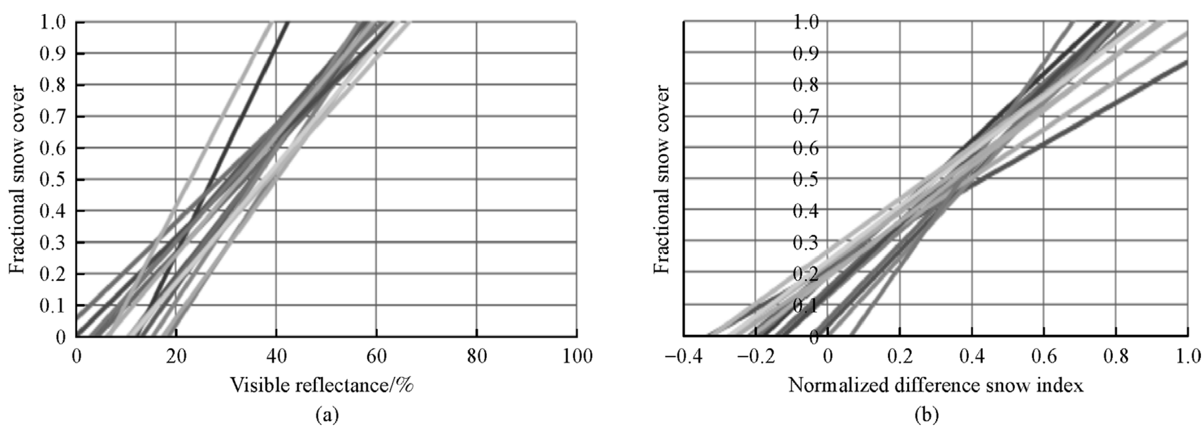

Fig. 8 Linear regressions of snow fraction on visible reflectance (a) and on NDSI (b).

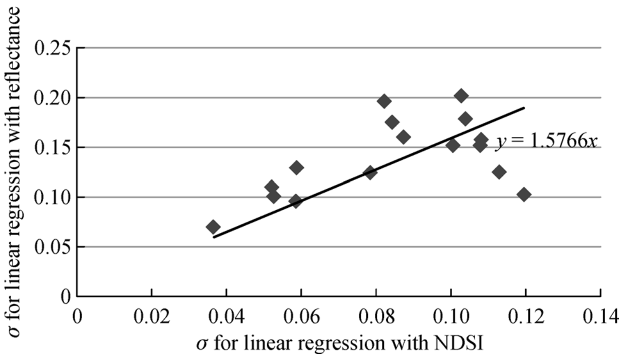

Fig. 9 Standard deviation (σ) for snow fraction regression on visible reflectance vs. standard deviation (σ) for regression on NDSI.

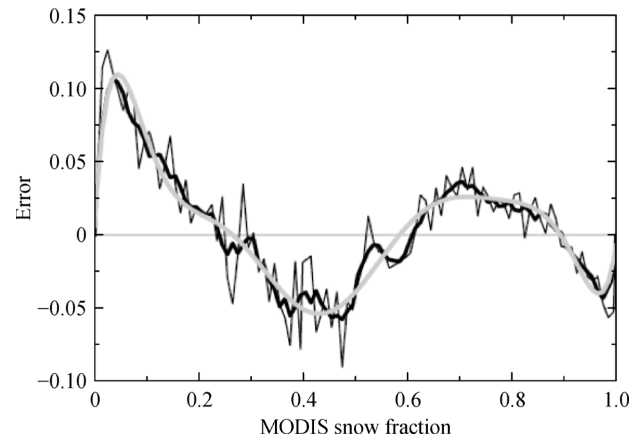

Fig. 10 The errors in the MODIS subpixel snow fraction estimates. Thick line denotes a five-point running mean, gray line is a polynomial approximation.

All those enhancements became possible only on the basis of using the MODIS snow cover fraction derived from a simple relationship in terms of the normalized difference snow index, supplemented by taking into account local scene-specific corrections to "universal" relationship between fractional snow cover and NDSI.

There are two goals of this catchment based study directly related to the subject of the current work

- to validate the subpixel snow fraction derived from MODIS observations and to tune the data to specific conditions under consideration;
- to apply the snow areal depletion curves to improve the quality of numerical simulations using parameter constrain in the model of land surface processes.

The validation of the NDSI approach to estimate the MODIS snow fraction was based on comparison with Landsat satellite imagery at a spatial resolution of 30 m that was considered to be ground truth. For the area under consideration the coefficients in Eq. (3) were estimated as a = 0.06 and b = 1.21. The quality of snow fraction estimate is characterized by the coefficient of correlation between retrieved snow fraction and ground truth R^2 = 0.90, a mean absolute error of 7% and a root-mean-square error of 12% in snow fraction.

A detailed analysis of errors made in (Déry et al., 2005a) illustrates stratified performance of the NDSI-based retrieval of snow fraction (Fig. 10).

The comparison of land surface processes simulation with field-based observations demonstrates that the land surface model using the subgrid-scale snow parameterization captures the timing and the amount of river runoff due to snow melt with more accuracy than without the subgrid scale snow parameterization.

5 Conclusions

The current study describes the development, improvements, validation, and applications of the method to retrieve fractional snow cover from satellite observations. The uncertainty of snow fraction estimates is evaluated through a quantitative comparison of the MODIS and VIIRS fractional snow cover products with high-resolution Landsat data as a source of ground truth in the vicinity of a snow line separating snow covered areas from snow free regions.

The NDSI-based algorithm takes into account two quite different types of variability in snow and non-snow reflective properties, characterized by very significant local changes within a scene as well as by marked changes in predominant values from one scene to another.

Significant sub-scene local variability in snow and non-snow reflective properties is accounted for by the Normalized Difference Snow Index with a high accuracy providing obvious advantages in comparison with using reflectances.

A globally applicable, linear statistical relationship between snow fraction and NDSI has been developed using analysis for a wide variety of natural conditions and tested in independent areas. It has been demonstrated that the fractional snow cover within a MODIS pixel can be provided with a mean absolute error of less than 0.1 over the entire range of 0.0–1.0. The correlation coefficient is near 0.9 and the mean-square-root error near 0.10. Somewhat better performance was found for the Terra MODIS versus the Aqua MODIS over nearly concurrently observed scenes.

The calculations using an uniform linear relationship between snow fraction and the Normalized Difference Snow Index illustrated a fairly robust determination of the MODIS snow fraction within 500 m cells, that withstands a significant variability in snow and non-snow properties.

Such a "universal" globally applicable relationship was implemented in NASA with the MODIS observations to provide daily global fractional snow cover output at 500 m resolution (Collection 5). The results of the NDSI-based fractional snow cover retrievals are validated and used extensively by the community as evidenced by hundreds of published papers that utilize the MODIS snow fraction product.

Taking into account the variability in reflective properties is used for tuning the linear relationship of the NDSI-based approach to local conditions optimizing the relationship to specific features of each individual image on the basis of adjusting the algorithm on the fly to predominant snow and non-snow characteristics.

A significant sub-scene heterogeneity can contaminate snow fraction derivation. To increase the accuracy of the algorithm, we assume variation of the endmembers on a pixel-by-pixel basis, which accounts for variation in surface types both for snow and non-snow NDSI endmembers. The pixel-to-pixel changes in NDSI endmembers are evaluated on the basis of analyzing the NDSI probability density function within a sliding window, including a subset of an image in the vicinity of each pixel. The adjustment of the parameters in snow algorithms to specific local conditions is an essential improvement leading to better quality of the NDSI-based VIIRS snow products.

The careful detailed validation of snow fraction for a variety of conditions provides valuable information on the reasons of retrieval errors and helps identify the directions to improve the snow products. The purposeful methodical validation, including into consideration the variability of snow and non-snow reflective properties, is a promising way to improve fractional snow cover algorithms and to create unbiased and consistent information on snow cover distribution required for global studies, regional and local scale hydrological applications.

The adjustable version of the algorithm varies from region to region and from time to time depending on snow and background surface state as well as on the viewing geometry. Testing the implementation of proposed enhancements shows that the algorithm employing scene-specific NDSI characterizing snow and non-snow reflective properties improves fraction snow retrieval.

The current study indicates that using scene-specific endmembers is a promising way to improve performance of fractional snow cover algorithms. The developed scene-specific approach offers further enhancement in comparison with previously published fractional snow cover algorithms created for global-scale use with moderate resolution remote sensing data.

The validation results demonstrate that, on the whole, the performance of the algorithms using the Normalized Difference Snow Index has advantages in comparison with other approaches, including the algorithm utilizing an individual reflective band. The retrieval based on the visible reflectance provides much poorer quality of snow fraction than the NDSI-based approach. The scene-specific realization of the NDSI algorithm is close to its optimal version and therefore could be preferable for snow fraction retrieval.

The results presented in this publication clearly identify that the improved quality of snow fraction estimates serves as promising development to assess snow water equivalent and changes in snow cover state contributing to better modeling of land surface and hydrologic regimes. The success of managing water resources will depend on coordinating described investigations with the works of other researchers developing further enhanced models.

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